Impact Assessment of Supply-Side and Demand-Side Policies on Energy Consumption and CO_2 Emissions from Urban Passenger Transportation: The Case of Istanbul

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Abstract

The transportation sector accounts for about a quarter of global energy consumption and energy-related carbon emissions. To design and realize sustainable urban transportation, it is vital to understand and analyze interactions between a set of dynamic factors that shape transportation patterns, behaviors, and impacts. To this end, this study aims to develop a systems dynamics (SD) model for Istanbul, Turkey to simulate its urban motorized passenger transport system for analyzing numerous policies under different scenarios and assessing their potential effects in reducing energy consumption and CO_2 emissions in the upcoming years. The constructed SD model includes four subsystems: population, household disposable income, transport, and energy and CO_2 emissions. Based on historical data (2000-2015) and model validation processes, the energy consumption and the associated CO_2 emissions from motorized passenger transport are forecasted for the following scenarios. The first one is business as usual scenario (BAU) which is designed to show how energy use and the associated CO_2 emissions would evolve over time with the current development plans. The second and third scenarios constitute supply management measures (SMM) which consider different levels of improvements in the fuel economy of the vehicle fleet and reduced carbon emission intensity in electricity generation through increased share of renewable energy use. The fourth and fifth scenarios consider travel demand management (TDM) policies that include different levels of transport cost increase, and trip length reduction. Finally, the last two scenarios include integrated scenarios that are composed of the SMM and TDM options. In detail, compared to the BAU scenario, integrated scenario considers (1) a 10% improvement in the fuel economy of the vehicles, (2) a 10% reduction in the emission intensity of electricity generation, (3) a 30% increase in the transportation cost, and (4) a 15% reduction in the trip lengths. Under the BAU scenario, the SD model shows that energy consumption per capita from passenger trips will increase from 183 liters of oil equivalent in 2016 to 315 liters of oil equivalent in 2025 while the associated CO_2 emissions per capita will increase from 460 kg in 2016 to 807 kg in 2025. To combat this dramatic growth, the findings indicate that the ambitious integrated scenario achieves the lowest energy consumption and CO_2 emissions by offering a 33.5% expected reduction in total energy consumption and a 32.8% expected reduction in total CO_2 emissions.

Keywords: Transport Policy, Energy, CO_2 Emissions, System Dynamics, Istanbul

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Highlights

- Development of system dynamics model for Istanbul passenger transport network
- Several supply-side, demand-side, and integrated policy scenarios are generated using cost, emission, and trip-related parameters
- Policies are evaluated based on transport energy consumption and CO_2 emissions for Istanbul until 2025.
- Integrated policies perform the best and lead to nearly one-third of energy and carbon emissions compared to business as usual case.

1. Introduction

Sustainable transportation is one of the essential elements of sustainable development as the transport sector is a major consumer of fossil fuels and a primary source of carbon emissions. Moreover, the transport sector leads to undesirable impacts such as land degradation, traffic congestion, air pollution, and the interruption of natural life. In 2014, the transport sector accounted for 26% of the world's total energy consumption and a similar proportion, approximately 22%, for the energy-related greenhouse gas emissions (IEA, 2016). In other words, 64% of the global primary oil consumption was used to meet 92% of the total energy demand in the transport sector (IEA, 2016). On the other hand, it is expected that final global fuel consumption will increase from 9,425 mtoe/year in 2014 to 12,244 mtoe/year by 2040 if no new or alternative supporting measurements are implemented as declared by the Paris Agreement (IEA, 2016). Similarly, the share of the transport sector in final fuel consumption is projected to reach 28% during the same period. This additional increase is triggered by several factors including projected population and economic growth and global trends towards urbanization and motorization rates. Furthermore, a sizable growth in transport-related energy consumption is expected in developing countries such as China, Brazil, India, Indonesia, Mexico, and Turkey (IEA, 2016).

Table 1: Top 20 cities with the worst traffic conditions at Tom-Tom Traffic Index (TOMTOM, 2016; UN-Habitat, 2016)

Rank	City	Population (million)	Congestion Level	Rank	City	Population	Congestion Level
1	Mexico City (Mexico)	21.1	66%	11	Changsha (China)	3.9	45%
2	Bangkok (Thailand)	9.4	61%	12	Los Angeles (the U.S.)	12.3	45%
3	Jakarta (Indonesia)	10.5	58%	13	Moscow (Russia)	12.3	44%
4	Chongqing (China)	13.7	52%	14	Guangzhou (China)	13.1	44%
5	Bucharest (Romania)	1.9	50%	15	Shenzhen (China)	10.8	44%
6	Istanbul (Turkey)	14.4	49%	16	Hangzhou (China)	9.2	43%
7	Chengdu (China)	7.8	47%	17	Santiago de Chili (Chile)	6.5	43%
8	Rio de Janeiro (Brazil)	13.0	47%	18	Shijiazhuang (China)	3.4	42%
9	Tainan (Taiwan)	1.9	46%	19	Buenos Aires (Argentina)	15.3	42%
10	Beijing (China)	21.2	46%	20	Kaohsiung (Taiwan)	2.7	41%

A historic milestone was achieved in 2007 when the global urban population surpassed the rural population for the first time (UN-Habitat, 2012). As of 2016, around four billion people live in cities and towns of which 512 cities have a population of at least one million inhabitants (UN-Habitat, 2016). More importantly, 31 of these cities have reached megacity status: an urban settlement hosting over ten million inhabitants (UN-DESA, 2014). Noting that there were only two megacities in 1950, most of today's megacities have evolved from the developing world as a result of rapid urbanization and population growth. It is also projected that another ten cities from the developing world will be added to the list of megacities by 2030 (UN-DESA, 2014).

The problems associated with increased urbanization rates such as inequity, inequality, poverty, inadequate housing and basic services such as clean water, electricity, heating/cooling, education and health, and pollution of all kinds become characteristics of megacities (Sorensen and Okata, 2010). For example, 27 megacities in 2010 were responsible for 9% of the global electricity usage, 10% of the gasoline consumption, 13% of the solid waste despite constituting 6.7% of the global population (Kennedy et al., 2015). Furthermore, in terms of urban transportation, megacities are with the worst traffic congestion conditions and 2016 rankings are reflected in Tom-Tom traffic index– a navigation company which releases an annual traffic congestion index for around 400 cities across the world (TOMTOM, 2016). Top 20 cities with the highest traffic congestion levels are presented in Table 1. Therefore, developing innovative, sound and long-lasting solutions to the challenges of megacities, especially in the developing world, is highly critical to reduce the pressure on the human health and quality of life, depletion of energy resources, and CO_2 emissions in addition to providing better living standards and livable cities for their inhabitants. In order to achieve low-carbon city development goals, various transport policies can be employed to tackle the increasing levels of energy consumption and CO_2 emissions. These include investment in technological progress such as alternative fuel vehicles or vehicle fuel economy improvement, expansion of public transport services, more investment in active transport, promotion of the use of greener modes and vehicles, encouragement of trip sharing and chaining, and discouragement of car use through travel demand management (TDM) policies. In addition, better land use management and urban planning policies also reduce overall travel demand. Given that each urban area has distinctive economic, spatial, demographic, and transport characteristics, the success of such policies, when implemented, varies from one city to another. It is noteworthy that sustainable urban transportation is not only a technical issue, but it also requires harmonization between organizations, decision-makers, society, and development actions by considering the interactions between people, nature, infrastructure, and technology. This requires understanding the dynamics of transportation to make reasonable projections under different scenarios. Thus, a systematic approach covering the urban transport sector from numerous aspects is needed to examine the effects of various transport policies.

Many complex systems such as the structure of a corporation, urban area, economic processes, or transport sector are constituted by a variety of variables which makes it difficult for decision-makers to analyze, predict, manage and control. System dynamics (SD), originally called industrial dynamics, is a methodology developed by Prof. Jay Forrester in the late 1950s to examine such large-scale, complex socio-economic systems (Forrester, 1958). SD provides a simulation platform to make integrated assessments and policy decisions under different scenarios over time (Saeed, 1994). Although early SD applications were mainly limited to industrial management, it has been applied to various fields throughout the years. Such fields include government policy (Forrester et al., 1976), healthcare (Homer and Hirsch, 2006; Lane et al., 2000; Royston and Dost, 1999), the automotive industry (Hayter, 1997; Kumar and Yamaoka, 2007), the electrical power industry (Ford, 1997), and urban studies (Duran-Encalada and Paucar-Caceres, 2009; Dyson and Chang, 2005; Forrester, 1970; Han et al., 2009).

In the mid-90s, SD was particularly suggested for the first time as a well-suited approach to strategic policy analysis and a support tool for decision making processes in the field of transportation (Abbas and Bell, 1994). Since then, numerous studies have proposed and applied

SD models for various purposes in the field (Shepherd, 2014). These studies vary extensively focusing on different aspects of transportation such as alternative fuel vehicles (Kwon, 2012; Onat et al., 2016; Stepp et al., 2009; Struben and Sterman, 2008), effect of resource allocation policies on urban transport diversity (Feng and Hsieh, 2009), linkage of transport development and land use (Shen et al., 2009), evaluating applications on traffic safety policy (Goh and Love, 2012), urban traffic and its parking related states (Cao and Menendez, 2015), air passenger demand forecasting (Suryani et al., 2010), impacts of rail transit system on metropolitan regions (Yang et al., 2014), highway sustainability (Egilmez and Tatari, 2012), intercity transportation (Han and Hayashi, 2008; Lewe et al., 2014), congestion pricing scheme (Liu et al., 2010; Sabounchi et al., 2014), and traffic congestion and air pollution linkage (Armah et al., 2010).

There are only a handful of studies in terms of energy use and associated emissions in urban transportation. These studies can be categorized into two main groups: (1) studies that employ preexisting SD models; and (2) studies that propose a new model specifically developed for their study contexts. The preexisting models for the first group include *Metropolitan Activity Relocation Simulator* (MARS) and *For Future Inland Transport Systems* (ForFITS). MARS is a dynamic land use and transport interaction model, which is capable of analyzing various transport policies at the city and regional levels (Pfaffenbichler et al., 2010). Pfaffenbichler et al. (2010) introduced the concepts underlying the model, MARS, and provided some examples of the model to show how the initial model developed for Vienna could be transformed to apply in another city, Leeds. When setting up a new model, the model requires a significant amount of data for calibration such as housing cost, income, living space, and share of owner-occupiers. Along similar lines, ForFITS, the product of the UN Development Account (UNDA), was developed to estimate transport emissions, and evaluate transport policies for CO_2 emissions mitigation (Andrejszki et al., 2014). While the model is suitable for the analysis of local, regional, and national transport systems, its primary focus is on national systems. As an example study to the local level, Menezes et al. (2017) used ForFITS to evaluate low-carbon urban development strategies for the transport sector in a Brazilian megacity, São Paulo. Their motivation to use ForFITS was to demonstrate the usefulness of the tool in the context of a megacity and produce internationally comparable results.

Using preexisting simulation models offers the following advantages. First, it is more time-efficient than developing a new model. Second, a team of experts in the field developed these models, so researchers can benefit from such built-in knowledge. Third, the models enable the researchers to compare its results with other cities on which similar studies conducted using such models, as it is not the case for the new models specifically developed for a study context. On the flip side, there are several disadvantages of using preexisting simulation models. Firstly, it may not always be possible to capture the characteristics of the study accurately because there is not much room to modify and change the built-in hypothesis and assumptions underlying preexisting models. Secondly, preexisting models require a significant amount of data to calibrate the model for a new study area. However, the data availability and collection standards are problematic for many cities across the world, which is another critical barrier in employing these models for every study context.

Studies that propose a new model specifically developed for their study contexts could be divided into two categories. The first category consists of the studies include urban transportation system as a subsector to study a broader sector. For example, the transport sector along with industry, agriculture, service and residence sectors are used to model the urban energy consumption and CO_2 emissions trends for the city of Beijing, China over the time period of 2005–2030 (Feng et al., 2013). Similarly, another model is proposed to estimate behavioral parameters affecting air pollution in Tehran, Iran by considering the sectors of urban transportation and air pollution industries (Vafa-Arani et al., 2014). Other studies can also be considered in this category include the study of (Fong et al., 2009) which proposes an SD model as a decision making tool to be adopted in the urban planning process on the case of Iskandar Development Region of Malaysia, and the study of (Du et al., 2018) in which the transport sector is studied along with the other seven sub-sectors for the case of Shanghai, China to evaluate carbon emissions trends during the period of 1991-2015, from the perspective of an urban planning system. Developed primarily at the city level covering numerous sectors in addition to the transport sector, these models often lack sufficient detail to capture the characteristics of the transport sector adequately. Therefore, these models may not seem appropriate to test the possible impacts of certain transport policies in terms of energy conservation and CO_2 mitigation in an urban setting.

To bridge the gap, new models with a primary focus on urban transportation system have been evolving, which are considered under the second category. Haghshenas et al. (2015) developed an SD model based on world cities data to analyze sustainable transportation dynamics for Isfahan, Iran, to evaluate different transportation development scenarios. While trip generation, modal share, transportation supply and equilibrium between supply and demand were the key modules of the developed model, the key outputs of the model involve various economic, social and environmental indicators including transportation energy consumption and associated air pollution. One of the main contributions of the paper was the developed database based on the existing global databases because most of the databanks in the field are in disorder and limited to city reports. Along the same line, another model is presented to explore the potential of different policy options in reducing vehicle fuel consumption and mitigating CO_2 emissions for Kaohsiung City in Taiwan with a time frame from 1995 to 2025 (Cheng et al., 2015). This model considers urban road transport modes including city buses, light-heavy trucks, motorcycles, and passenger cars, and utilizes vehicle miles traveled and a number of vehicles for each mode to calculate associated energy consumption and CO_2 emissions. One of the main difference of the paper compared to the previous studies is that the authors considered *household disposable income* over *Gross Domestic Product (GDP) per capita* in their model, which is believed to be a better indicator in reflecting the economic factors on car ownership levels (Wu et al., 2014).

In reference (Xue Liu et al., 2015), a model was built for Beijing, China with a particular focus on urban passenger transport based on the number of trips by each mode available in the city. A scenario-based analysis of numerous policy options was made for urban passenger transport energy consumption and CO_2 emissions for the time period from 2002 to 2020. This model includes four different subsystems: an economy subsystem, a population subsystem, a transport subsystem based on trips generated by each transport mode, and energy consumption and CO_2 emissions subsystem. In another study for Beijing, a different model was constructed to study the impact of different strategies on urban traffic's energy consumption and carbon emissions (Wen and Bai, 2017). Although both models were built for Beijing's urban transport system and there are several overlaps, their structures were designed differently. Because they intended to test different policies thus requiring a different setting to include specifically tailored variables for those policies. In addition, for the case of Latin America, a similar model was presented to estimate passenger transport emissions of local pollutants and CO_2 by integrating land use and transport sectors for Bogota, Colombia within the time period from 2010 to 2026 (Guzman and Orjuela, 2017).

All of these studies have selected an urban area to test their proposed SD model. One apparent reason behind this is that each urban area has distinctive spatial, demographic, and transport-related characteristics. Hence, a specific model based on the scope of the research problem is usually required. Given the complexity of transport dynamics in large cities, it is still believed that there is still limited research on energy consumption and the associated emissions from urban passenger transport and this context is not well understood; thus, more efforts are needed (Li et al., 2018; Xi Liu et al., 2015). To the best of the authors' knowledge, Istanbul is such a place where the impact of transport policies on energy consumption and CO_2 emissions levels have not yet been studied sufficiently. Therefore, any attempt to investigate transport system of such a large city from these aspects is highly beneficial for understanding the dynamics of the city and contributes to the existing literature by enriching the SD applications in the field. This study provides investigations on passenger transport-related energy consumption and CO_2 emissions in Istanbul, the megacity of Turkey, and focuses on the following research questions:

Q1. If the status quo is maintained, how will this affect future energy consumption and CO_2 emissions levels?

Q2. What additional supply-side and demand-side policies should be considered in achieving reduced energy consumption and CO_2 emissions in Istanbul?

To this end, a systematic approach covering numerous aspects of the transport sector – which include demographics, economic growth, motorization rate, the attractiveness of transport modes, energy consumption, and CO_2 emissions – is needed to understand the dynamics of transportation, examine the effects of various transport policies and make projections under different scenarios. SD is identified as such an approach, which has increasingly been used in the field. Therefore, this study aims to develop a systems dynamics (SD) model for Istanbul, Turkey to simulate its urban motorized passenger transport system for analyzing numerous policies under different scenarios and assessing their potential effects in reducing energy consumption and CO2 emissions in the upcoming years.

Overall, the outcomes of this research are intended to contribute to better decision making and city planning in Istanbul, and consequently, help Turkey to meet its Paris Agreement goals as well as achieve better urban life in Istanbul. This research can also help to expand the understanding of the problems associated with the energy consumption and CO2 emissions from the passenger transport in the context of the other megacities from the developing countries. Additionally, the present study contributes methodologically to the field in two ways. First, Istanbul comprises a variety of the transport means for passengers (i.e., car, shuttle, bus, rail, bus rapid transit (BRT), sea lines, jitney, taxi, and minibus) unlike many other cities; therefore, this study will be among the first attempts to consider such a variety of transport means in modeling the transport system of a large city. Second, the developed model presents a ‘desire-to-drive ratio’ variable to account for the changes occurred in the travel behavior of residents in response to the changes occurring in the transport cost.

The remaining of the paper is organized as follows. Next section presents the overview of the study area and introduces the method for how an urban motorized passenger transport SD model for Istanbul was developed with related data acquisition strategies, assumptions and scenarios based on the variation of specific parameters. The third section provides and interprets results of energy consumption and CO2 emissions of each scenario along with further discussions. Finally, the last section presents key conclusions and shortcomings of the research and points out potential future research areas.

2. Methods

2.1. Overview of the study area: Istanbul, Turkey

Our study is focused on Istanbul, which is a Turkish megacity, and the economic, financial, industrial, and cultural center of the country. Because the city hosts approximately 18% of the country’s population, concentrates 27% of national GDP, accounts for 18% of national energy use, produces 38% of total industrial output and more than 50% of services, and generates 40% of total national tax revenues (EPDK, 2017; OECD, 2008), it is accepted as the most important part of the country. Similar to the other megacities of the developing world, Istanbul has witnessed a tremendous population and motorization growth in the last few decades. The population of Istanbul was just 4.7 million people in 1980, before increasing to 11 million people in 2000 and finally reaching 15 million people in 2015. The motorization growth is even more dramatic. While the number of vehicles in the city was only 0.2 million in 1980, it first increased to 1.25 million in 2000, and then to 3.6 million in 2015. To put it another way, the number of vehicles in the city has grown almost six times faster than the population growth in the given time period. This uncontrollable growth both in population and the number of vehicles has caused severe transport-related problems, and thus overall life quality-related problems. In terms of traffic congestion, for example, Istanbul was ranked as the sixth worst city among 390 cities around the world in 2016 (see Table 1). Additionally, it fared very poorly in the European Green City Index, an index which assesses and rates environmental impact of 30 major cities in Europe (Shields and Langer, 2009). Istanbul’s overall ranking was 25th in the list in 2009 with a score of 45.30 out of 100, while it was ranked 23rd for both transport and air quality categories, and 29th for environmental governance, the category in which the city scored the lowest.

Table 2: Sustainable Transport Indicators in Turkey (2000-2012) (Turkstat, 2016a)

	2000	2005	2010	2012
Total final energy consumption (thousand tons of oil equivalent)	61,556	71,510	83,367	89,008
Total transport energy consumption (thousand tons of oil equivalent)	12,008	13,849	14,925	20,471
Road transport energy consumption	10,509	11,785	13,258	18,525
Greenhouse gas emissions from transport (thousand tones CO_2 equivalent)	35,516	41,307	45,142	~61,863
CO_2 emissions per inhabitant (tones per capita)	3.5	3.8	4.5	4.7
Motorization rate (cars per one thousand inhabitants)	69	84	102	114
Modal split of passenger transport (%)				
Passenger cars	49.1	55.5	59.3	59.4
Motor coaches, buses and trolley buses	47.7	42.1	38.3	38.1
Trains	3.2	2.4	2.4	2.5

As a signatory of the Paris Agreement, Turkey agreed to do its part to reduce greenhouse gas emissions to combat global warming and climate change. When viewed from this aspect, the transport sector of Turkey is an important element in this picture. Table 2 presents indicators of sustainable transport in Turkey from 2000 to 2012. As depicted in this table, transport share in final energy consumption for Turkey has increased from 19% (12,008 toe of 61,556 toe) in 2000 to 23% (20,767 toe of 89,008 toe) in 2012. More than 88% of transport energy consumption is consumed mainly by passenger transport. Moreover, greenhouse gas emissions stemming from the transport sector have increased from 35,516 thousand tones CO_2 equivalent in 2000 to 47,946 thousand tones CO_2 equivalent in 2012 with a growth rate of 35%. During the same period, CO_2 emissions per inhabitant have also increased at a rate of 34%. From the viewpoint of Istanbul, the city's car ownership level is still low (around 168 cars per 1000 people) when compared to the cities of the developed world (400-500 cars per 1000 people), thus resulting in low per-head energy consumption (Turkstat, 2016b). Projections show that the number of cars will reach 4.3 million by 2023 (252 cars per 1000 people), which indicates even worse energy and carbon emissions figures in the upcoming years along with the other severe transport related problems such as traffic congestion (Batur and Koç, 2017; IMM, 2011). Therefore, Istanbul's role is highly crucial for Turkey in this mission of achieving the Paris Agreement goals.

Under the pressure of unbearable traffic congestion, growing energy demand, foreign oil dependency, increasing air pollution and other transport-related issues within the city, massive investments are required to upgrade Istanbul's transportation system. Istanbul Metropolitan Municipality (IMM) has planned to invest 36 billion USD in the transport system from 2010 to 2023 in addition to substantial investments made during the last decade (IMM, 2011). With respect to this, billions of dollars' worth of infrastructure and service projects for both public transportation and passenger car transport are being realized in the city. Such projects include introducing a new BRT network, expanding the railway network from approximately 100 km to 420 km by 2019, building the third bridge across the Bosphorus, two undersea tunnels for railway and cars, increasing public transport patronage, improving public transportation service quality, and promoting public transportation usage. These efforts have been shaping the city's transport figures. In addition to that, travel demand increases in parallel with GDP per capita growth in the city. While the number of daily trips was 1.81 per person in 2009, projections show that it will increase to 2.03 daily trips per person by 2023 (IMM, 2011). Figure 1 illustrates the changing landscape of urban motorized travel modal split for 1996, 2006 and 2012.

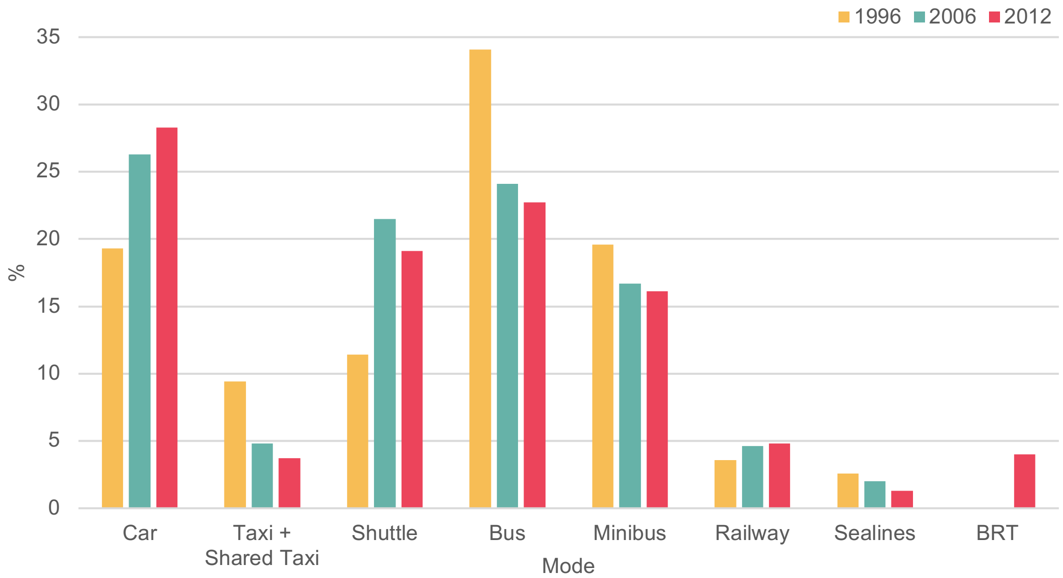

Figure 1: Modal split of Istanbul in 1996, 2006, and 2012 (Gerçek and Demir, 2008; IMM, 2015)

2.2. Model formulation

System dynamics (SD) is a computer-aided approach for understanding the behavior of complex systems over time. The SD approach, which is based on feedback control theory, utilizes feedback loops, variables, and equations. A closed chain of causes and effects in a bounded system is defined as the feedback loop. The variables can be classified in two ways: (1) stock (level), flow, and auxiliary variables; and (2) endogenous (i.e., arising from within) and exogenous (i.e., arising from without). In the first classification, (1) stock (level) variable is the one that accumulates a flow over continuous time periods; (2) flow variable is the one that represents the rates of increase or decrease in stock variables during a time period; (3) auxiliary variable is the one that identifies flow variables. In the second classification, endogenous variable is a dynamic variable involved in the feedback loops of the system whose value is determined by the states of other variables in the system; for example, changes in population or economic conditions of a city can be used to explain the changes in travel demand. On the contrary, an exogenous variable is a component whose value is not directly affected by the system but determined by factors or variables from outside the boundary of the system. For example, changes in population are affected by many factors including birth rates, death rates, migration rates, so such factors can be treated as exogenous variables. These variables are linked by different equations in the form of integral, differential or other types.

2.2.1. System boundary

The focus of this study is the problems associated with the increasing CO_2 emissions trend in Istanbul, Turkey. Due to various reasons such as increasing energy consumption in transport, motorization rate and travel demand, CO_2 emissions caused by the transport sector in Turkey exhibit an increasing pattern in the last decade (see Table 2). Istanbul constitutes the main contributor to this increase because, as of 2016, it accommodates 18% of the total population of Turkey and 24% of its total registered cars (Turkstat, 2016c, 2016b). There are many factors affecting CO_2 emissions in the transport sector such as population, economy, travel demand, modal share, and energy consumption (Timilsina and Shrestha, 2009). Hence, these main parameters are identified prior to the construction of the causal loop diagram (CLD) in the light of the research objectives, data availability and the previous studies in the field (Cheng et al., 2015; Egilmez and Tatari, 2012; Xue Liu et al., 2015). The data between 2000 and 2015 was analyzed to calibrate and verify parameters to use in our simulation model for the period between 2015 and 2025. The overview of these parameters is given in Appendix B. After identification of parameters, the next step in modeling was to construct CLD. Vensim 7.0 software was used to construct CLD and further diagrams and analysis for this study (Vensim, 2017). The constructed CLD is given in Figure 2, which shows cause and effect relationships among the parameters. The relationships are determined by feedback loops according to the existing literature in the field (e.g., Cheng et al., 2015; Guzman & Orjuela, 2017; X. Liu et al., 2015). Each arrow indicates the influence of one parameter on another where a positive (+) sign indicates positive relation such that an increase (or decrease) in one element causes an increase (or decrease) in another element. Similarly, a negative (-) sign indicates a negative relation such that an increase (or decrease) in one element causes a decrease (or increase) in another element. In other words, a positive sign indicates reinforcing impact whereas a negative sign indicates a balancing effect. In addition to that, a solid line in CLD is a direct relationship while a dotted line is an inverse (information based) relationship. Accordingly, the following causal loops have been considered within our system boundary, where the arrows indicate the direction of causes from one element to another:

- Economy → Household disposable income → # Car → Car trips → Energy consumption → CO_2 emissions → Economy

- Economy → Household disposable income → Passenger travel demand → Car trips → Energy consumption → CO_2 emissions → Economy

- Economy → Household disposable income → Passenger travel demand → Public transport trips → Car trips → Energy consumption → CO_2 emissions → Economy

- Economy → Household disposable income → Passenger travel demand → Public Transport trips → Energy consumption → CO_2 emissions → Economy

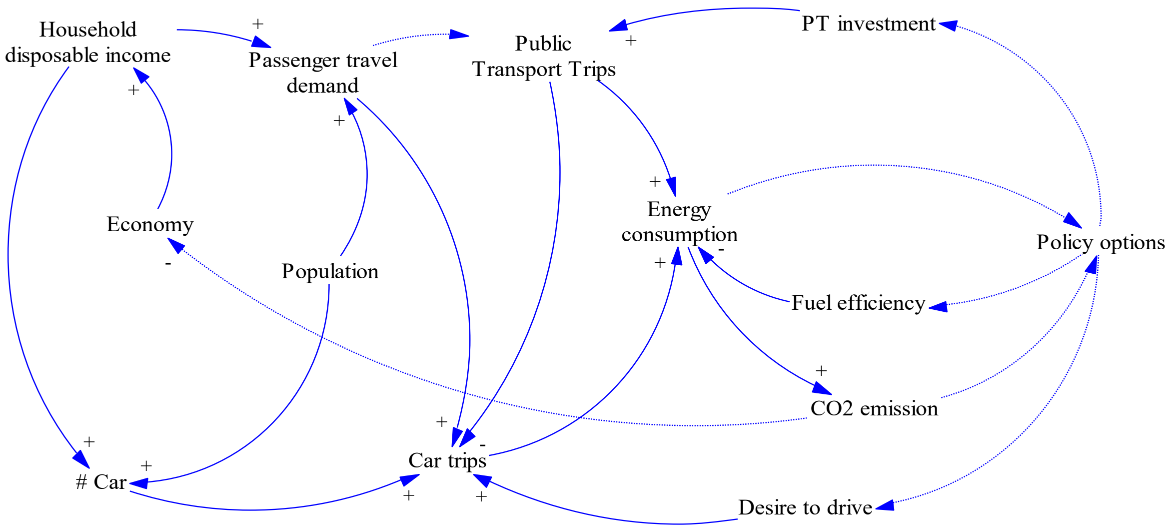

Figure 2: Causal Loop Diagram

2.2.2. System structure

After identifying the system boundary, the next step is constructing the system structure. In order to that, first, sub-models are developed for the parameters. Population and household disposable income might be affected by changes in overall travel demand and trip making characteristics and consequent changes in energy consumption and associated emissions. However, these feedbacks are likely to be small over the selected time horizon; thus, population and household disposable income are assumed as exogenous variables and detailed sub-models are not included. Other parameters are defined as endogenous, so detailed sub-models are included in the model with stock (level), flow and/or auxiliary variables as required. Accordingly, the stock and flow diagram, which is the quantitative analysis model of the system based on the identified causal loops, is constructed (see Appendix A). In total, our model consists of 9 stock (level) variables, 9 flow variables, and 70 auxiliary variables. Breaking down a system into multiple subsystems is an easy way to convey its hierarchical structure. With regards to this, our model can simply be divided into four subsystems: population, household disposable income, transport, energy consumption, and CO_2 emissions.

Population subsystem

The population of Istanbul has increased from approximately 11 million people in 2000 to 15 million in 2015, and it is expected that it will surpass 17 million people by 2025 (Turkstat, 2016c). In our model, the population is considered as an exogenous variable. The look-up table approach is employed to input the population information into the model. In addition to that, the floating population into the city has been, on average, 40 thousand per annum in the last decade (Turkstat, 2016c), and thus an extra variable is not included for it. Instead, it is reflected as embedded in the population growth rate.

Household disposable income subsystem

Economic conditions of a city and its residents play an essential role in their mobility behaviors. In respect of personal car ownership, in particular, it is widely accepted that people tend to own a car when their income increases (Dargay et al., 2007). In Istanbul, the number of cars per thousand people has increased from 106 in 2000 to 168 in 2015 and it is expected to grow to the level of 252 cars per thousand people by 2023 (see Figure 3). Household disposable income and GDP per capita are two of the many key economic indicators to gauge the overall state of the economy. To reflect economic factors in our model, household disposable income is considered over GDP per capita in line with earlier studies (Cheng et al., 2015; Huo and Wang, 2012). Because GDP per capita may fall short of accurately measuring people's living standards, and thus growth in household income may evolve differently from GDP per capita (Boarini et al., 2006). Yet, it should be also noted that there is a strong correlation between household income and GDP per capita (Boarini et al., 2006). With regards to this, household disposable income is considered as an exogenous variable and include in our model as a stock variable which depends on the growth rate of GDP (Dargay et al., 2007). Furthermore, the growth rate of GDP is included in our model because the future projections on the economic conditions of Istanbul are only available on the growth rate of GDP, which is necessary to enable our model for making future projections towards the research objectives. GDP growth rates and household disposable income data has been obtained from the Turkish Statistical Institute (Turkstat, 2016d) and the Economic Policy Research Foundation of Turkey (TEPAV, 2016). As for the future outlook, GDP of Istanbul is estimated to grow with an annual rate of 4.2% by 2025 (PWC, 2009). In addition to these, the look-up table approach in Vensim is employed to reflect the GDP growth rate on household disposable income in our model.

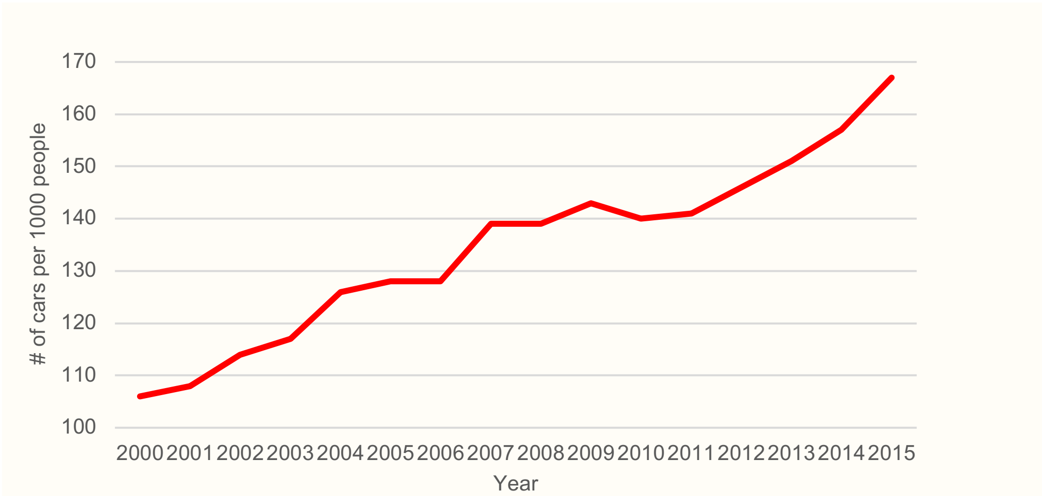

Figure 3: Car ownership levels in Istanbul, Turkey between 2000 and 2015 (Turkstat, 2016b).

Transport subsystem

During the last decades, total passenger trip volumes in Istanbul have increased as a result of population and economic growth and expanding city area (i.e., urban sprawl). As part of Istanbul Transportation Master Plan, it was estimated that the total number of passenger trips has increased from 21 million trips per day in 2006 to 24 million trips per day in 2009. By 2023, it is expected that total passenger trips will reach 35 million trips per day. In the same time period, daily trips per person are expected to increase from 1.74 trips in 2006 to 2.03 trips in 2023 (IMM, 2011). While the share of motorized trips in total passenger trips were 51% in 2009, it is expected that it will increase to 74% by 2023. This is mostly because of the fact that trip distance has been increasing due to the expansion of the city area; therefore, it has been substituted by motorized means, primarily by cars. The share of car trips in total motorized trips increased from 19% in 1996 and 26% in 2006 to 28% in 2012 (see Figure 1). It is also expected that this figure will be as large as 40% by 2023 (IMM, 2011). This continuing increase in the modal share of car trips has been changing transport figures irrevocably, which has been reflected in transport-related problems in Istanbul such as congestion and air pollution. In order to combat this challenge, the Istanbul Metropolitan Municipality (IMM) has planned to invest in railways, BRT and improving the bus service. Under these vast uncertainties, a transport subsystem is included in our model.

The two most common approaches to construct transport subsystems to estimate energy consumption and emissions from urban passenger transport are: (1) using vehicle fleet, vehicle kilometer travelled (VKT), fuel economy, and emission rates (Cheng et al., 2015; Egilmez and Tatari, 2012) and (2) using number of trips by each mode (modal share), driving distance, energy consumption per trip by each mode and emission rates (Lewe et al., 2014; Xue Liu et al., 2015). In this study, the second approach is used in constructing the transport subsystem. In Istanbul, the transport means for passengers are car, shuttle, bus, rail, sea, jitney, taxi and minibus (see Appendix A). For each mode, a stock variable is included in the transport subsystem:

Car trips: The main factor affecting car trips is the number of registered cars in the city and annual passenger trips per car. People tend to own a car for various reasons including benefiting from more rapid, flexible, comfortable, personalized, and reliable journey cars arguably offer compared to the other competing modes, expressing their social status through cars or lacking alternative transport options in their neighborhoods. Despite these reasons, studies indicate that the number of cars in a city is closely associated with population and income growth (Dargay et al., 2007; Stopher, 2004). Let X_1 denote the population and let X_2 denote household disposable income. Then, the number of cars in the city per annum can be estimated by the following linear least-squares regression

$$Y_1 = 2381006 - 0.12 \times X_1 + 114 \times X_2, \ (\mathrm{R}^2 = 0.99), \tag{1}$$

where Y_1 represents number of private cars. Transportation cost is an important factor in travel choice of people (Brueckner, 2005). Therefore, a variable, *desire to drive ratio*, is introduced based on a fraction between transportation cost and household disposable income. This variable is, then, used to reflect the effect of transportation cost on driving choices in estimating annual passenger trips per car. By denoting transportation cost by M, the desire to drive ratio Z can be calculated by

$$Z = X_2 / M \tag{2}$$

If transportation cost increases more than the household disposable income, the desire to drive ratio decreases. This means that people are required to allocate more money from their income to transportation. On the contrary, if household disposable income proportionally increases more than transportation costs, the desire to drive ratio increases. Data for transport cost has been obtained from the Turkish Statistical Institute's annual income and living conditions surveys (Turkstat, 2016d), which covers the expenditure on the purchase of both brand new and second hand vehicles, motorbikes, bicycles, spare parts and accessories, fuels and oils, maintenance and reparations, passenger transportation fares, and other transport services. In addition to that, population (X_1) and household disposable income (X_2) used to forecast annual passenger trips for each year with the following linear regression equation

$$Y_2 = -1449988629 + 382 \times X_1 + 100380 \times X_2, (\mathrm{R}^2 = 0.99), \tag{3}$$

where Y_2 denotes annual passenger trips forecast. Another important factor in determining annual passenger trips per car is total rail and BRT trips because both means provide an opportunity for car drivers to escape from traffic congestion. Therefore, it is assumed that rail and BRT means are the only PT options in attracting drivers based on the analysis of the past trends. In order to estimate annual passenger trips per car that is denoted by Y_3, the following linear regression formula is used:

$$Y_3 = 709 - (1.01\mathrm{E}-08) \times \mathrm{X}_3 + 3.97 \times \mathrm{Z} + (9.03\mathrm{E}-09) \times Y_2, (\mathrm{R}^2 = 0.96), \tag{4}$$

After all, car trip volumes are estimated based on the product of the number of cars and annual passenger trips per car.

Rail transit trips: Railway is an efficient and sustainable transport option for cities, especially for megacities. The length of the railway network in Istanbul was only 40 km in 2000, before being extended to 142 km by 2015 as the city had grown in terms of both area and population (IMM, 2018a). According to the plans of IMM, it is expected that the railway network of the city will be expanded to the total length of 700 km by 2030. This will, of course, have a considerable impact on the trip characteristics in the city. Liu et al. (2015) have considered initial rail length, rail length increase, initial rail transit passenger trip per km and rail transit passengers increase per km to calculate rail transit trips. A similar approach is followed for constructing rail trips sector in our model (see Appendix A). The required data for parameters of rail transit trips sector has been obtained from the Istanbul Metropolitan Municipality. The specific equations and detailed explanations for each parameter are given in Appendix B.

Bus rapid transit (BRT) passenger trips: Istanbul BRT system, Metrobus, was introduced to the city in 2007, and accounts for 4% of the modal split in 2012 (see Figure 1). The system length was around 18 km at the beginning, then it has extended to 30 km in 2008, 42 km in 2010, and finally 52 km in 2012. Today, it operates on a system which has 8 routes and 44 stations and has a fleet size of 535 vehicles (IETT, 2017a). Not only has the system offered an alternative travel option to the residents, but it has also contributed to reducing the number of private vehicles on roads parallel to the metrobus routes. In addition to that, it is planned to introduce an additional 50 km long BRT system to the city by 2020. The same approach with rail transit trips is followed in building BRT passenger trips sector in our model. The specific equations and detailed explanations for each parameter are provided in Appendix B.

Bus passenger trips: Istanbul's bus system remains the main component of the public transportation service in the city despite the decline in its share in modal split in the last decades.

As of 2016, it accounted for 24% of trip volumes of the entire public transportation system according to the statistics of the Istanbul Transport Authority (IETT, 2017b). This is lower than its share (32%) in 2006 (IMM, 2011), which is mostly because IMM plans to meet the increasing travel demand by railway and BRT options (IMM, 2011). The number of buses and routes have nearly been constant in the city over the last two decades. Only frequency and number of buses in operation have slightly been changing in order to adjust to the variations in trip characteristics. Therefore, the bus passenger trips sector is modeled based on the size of the bus fleet in operation and trip growth per bus per year. The details of parameters and equations in this sector are given in Appendix B.

Shuttle passenger trips: Dedicated shuttles to workplaces and schools in Istanbul have been very common as address-based school placement or school travel plans are not enforced and workplace choice varies considerably, not necessarily based on home location. It accounts for 19% of the modal split as of 2012. From another perspective, it represents around 32% of total home to school and home to workplace trips in 2010 (IMM, 2011). The number of shuttles is fixed by the municipality and no further licensing is on the agenda. Shuttle passenger trips is considered in our model by including shuttle trips growth rate per year. The future expectations and required data have been obtained from the Istanbul Metropolitan Area Transport Master Plan (ITMP) as well as from other institutions of IMM. The specific details of this sector in our model can be found in Appendix B.

Minibus passenger trips: The share of minibuses in the total public transportation has decreased from 20% in 1996 to 16% in 2012 (see Figure 1). The number of minibuses is also constant in Istanbul and currently, there is no plan to register new minibuses (IMM, 2011). The required data for this sector has been obtained from ITMP as well as from other institutions of IMM. The details of this sector are given in Appendix B.

Sea passenger trips: Unlike many other megacities, sea lines in Istanbul are quite important and have arguably high potential in providing mobility between both sides of Istanbul. Sea lines, however, represent only around 2% of the modal split in 2012. Since the opening of an undersea tunnel (Marmaray) in 2013 for railways, its share has been slightly decreasing (Çancı et al., 2015). However, IMM plans to sustain sea lines in order to meet the increasing travel demand of the city. A similar approach to minibus and shuttle sectors is followed in constructing the sea passenger trips sector. The required data and future expectations have been obtained from the work of Çancı et al. (2015) and IMTP as well as from other institutions of IMM. The details are given in Appendix B.

Taxi and jitney (shared taxi) passenger trips: Trips made by taxi and jitney represent a total of 4% of the modal split in the city. The number of taxis and jitneys are fixed in Istanbul and there is no plan to register new taxis or jitneys so that the increase in these means occurs in line with the increase in total passenger trips. No stock variable is included for both sectors; instead, they are reflected in our model using auxiliary variables. On the other hand, shared trip platforms like Uber are banned in Istanbul so that they are not considered in our model. The required data has been obtained from different sources including IMM reports and Bitaksi (an online taxi calling platform). The details can be found in Appendix B.

Energy consumption and CO_2 emissions subsystem

Car trips and taxi trips are distinguished from the other modes. Our analysis on past data indicates that energy consumption per trip by modes, which have fixed routes such as railway, BRT and bus, have been constant over the years. On the other hand, modes that do not have fixed routes (car, taxi, and shuttle) indicate different levels of energy consumption for each trip, thus distance per trip is used to calculate total energy consumption for these modes. Therefore, two different formulas are used to estimate energy consumption for each mode.

The specific formula for car, taxi and shuttle trips is as follows:

$$EC_{i,j} = C_{i,j} \times D_i \times TT_i, \tag{5}$$

where $EC_{i,j}$ provides energy consumption for *i*'th mode with *j*'th energy type while $C_{i,j}$ represents energy consumption per unit distance by i'th mode with *j*'th energy type; D_i represents trip distance by *i*'th mode; and TT_i represents total number of trips by i'th mode.

The specific formula for the other modes as follows:

$$EC_{i,j} = C_{i,j} \times TT_i, \tag{6}$$

where $EC_{i,j}$ provides energy consumption for *i*'th mode with *j*'th energy type while $C_{i,j}$ represents energy consumption per trip by *i*'th mode with *j*'th energy type, and TT_i represents total number of trips by *i*'th mode.

After overall energy consumption for each mode is obtained through the relevant calculations, the total energy consumption is calculated as follows:

$$TEC = \sum_{i,j}^{n,m} CC_j \times EC_{i,j}, \tag{7}$$

where TEC is total energy consumption; CC_j is a conversion coefficient to convert *j*'th energy type to oil; and $EC_{i,j}$ is energy consumption for *i*'th mode with *j*'th energy type.

Finally, the following formula is used to calculate total CO_2 emissions:

$$TCE = \sum_{i,j}^{n,m} EF_j \times EC_{i,j}, \tag{8}$$

where TCE provides total CO_2 emissions while EF_j represents emission factor from *j*'th energy consumption and $EC_{i,j}$ represents energy consumption for *i*'th mode with *j*'th energy type.

The emissions factor from energy consumption and CO_2 emissions and conversion coefficient are set according to the Intergovernmental Panel on Climate Change's (IPCC) guidelines. Appendix B includes the specific details of this subsystem along with the coefficient values. It is also important to mention that our approach has similarities with the work of Liu et al. (2015) in estimating the energy consumption and CO_2 emissions. Although both methods have similarities, since our work has a different scope, it is found unnecessary to follow the same notation.

2.3. Scenarios

Elements of mobility and access management for cities are categorized into three main categories (Meyer, 1997): supply management measures (SMM), land use management (LUM) and travel demand management (TDM) (see Figure 4). SMM include expanding the transportation network such as the road and PT network, traffic engineering, technological progress such as clean and green vehicles or improved fuel efficiency. LUM is simply concerned with how the land is used, and include issues such as construction permits according to different sets of human activities to be conducted in the related location. TDM aims to influence people to change their travel behaviors or to reduce the need to travel for the desired purpose through different sets of soft and hard measures such as fuel tax, congestion charging, workplace travel plans, car clubs, and awareness campaigns.

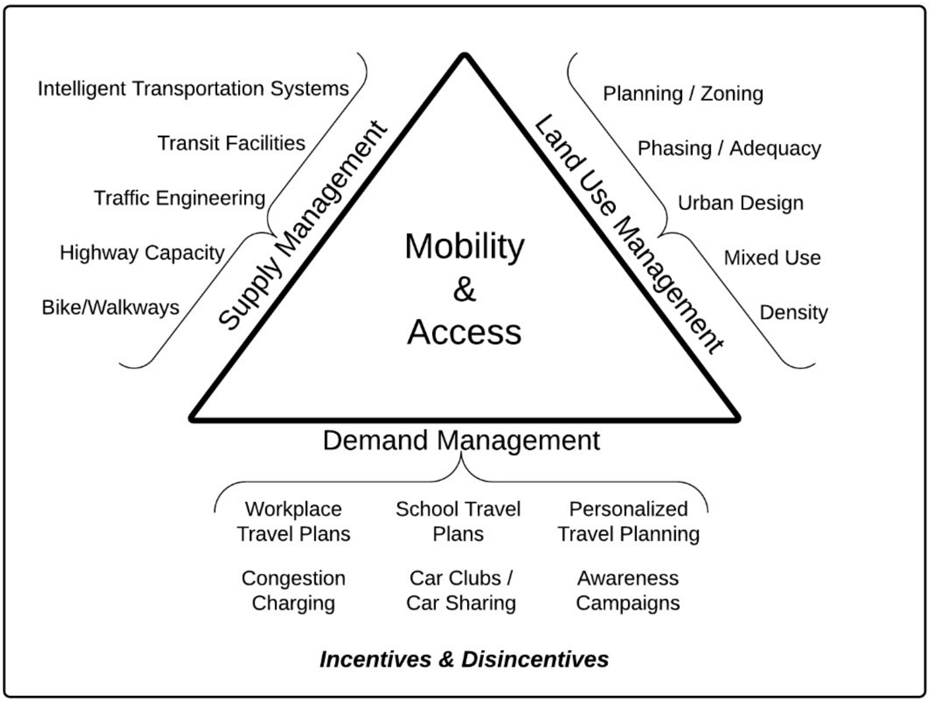

Figure 4: Elements of mobility and access management (reproduced)(Meyer, 1997)

Of these three groups, SMM policies are arguably the most common response in attempting to solve the problems in the transport sector. Much effort for low carbon transitions of the transport sector have, therefore, devoted to SMM policies to achieve the GHG reduction goals (Mandell, 2009; Moriarty and Honnery, 2008). While the large-scale uptake of SMM policies, especially low carbon technologies is crucial; many studies, however, come to a conclusion that they alone do not lead reduced GHG emissions targets (Bristow et al., 2008; Pye and Daly, 2015).

Therefore, in addition to SMM policies, TDM policies attract much attention because they offer significant potential for reducing energy demand by influencing people's travel behavior in such a way that travel demand is reduced or redistributed in space or in time and travel mode is shifted to a more sustainable means of transport. Given that each urban area has distinctive economic, spatial, demographic and transport characteristics, the success of such policies when implemented varies from one city to another. In Istanbul, the role and potential of such policies to mitigate traffic congestion issues of the city has been studied (Batur and Koç, 2017); however, their potential for reducing energy consumption and GHG emissions have not been considered thus far.

In this regard, this study attempts to fill this gap with a focus on both supply-side measures, which include improved fuel economy of vehicles and increasing share of renewables in energy source mixture for electricity generation, and demand-side measures, which include increasing transportation cost and reduced trip lengths. Within the scope of this study, our scenarios are built with policies from supply management and travel demand management because land use management is hardly applied to existing cities in a broader context. Before moving to these scenarios, first, a business as usual scenario is needed to set in accordance with the current development plans so that the effectiveness of the other scenarios can be compared in reference to this base scenario.

2.3.1. Business as usual scenario (BAU)

The business as usual scenario is set with the current development plans of the city. The details of this scenario are as follows:

- GDP of Istanbul is estimated to grow at a yearly rate of 4.2% until 2025 (PWC, 2009).
- The population of the city is expected to slightly surpass 17 million by 2025 (Turkstat, 2016c).
- It is assumed that the transport cost grows at the same rate as individual disposable income, so the desire to drive ratio will be similar to historical patterns.
- The rail network length is set to increase from 142 km to 502 km by 2025 according to IMM (2011). In addition to that, it is planned to expand BRT network from 52 km to 100 km by 2025 through the construction of another BRT line to be open by 2020.
- Expected growth rates of all PT means have been obtained from IMM (2011).
- Expected trip lengths for PT, car, and shuttle means have been obtained from IMM (2011).
- It is targeted that the fuel economy of light-duty vehicles must improve by 3.7% per year by 2030. Both historical and expected fuel economy data for light-duty vehicles have been obtained from GFEI (2017).

- It is assumed that energy consumption per PT trip will remain constant for each means in the upcoming years. Since energy is one of the main costs in the public transport sector, this assumption is made to ensure the economic viability of PT means.

2.3.2. Supply-side management measures (SMM)

Among various supply-side measures, only consider rail emission factor and fuel economy of vehicles are considered. Rail emission factor (CO2 emissions per kWh) is considered as emission intensity of the electricity generation, which is completely dependent on energy source mixture for electricity generation; thus, increasing the share of renewables in this figure would contribute to reducing the rail emission factor. On the other hand, technological progress directly contributes to improving the fuel economy of vehicles. Although a significant improvement is expected on the fuel economy side under BAU scenario, it is assumed that more improvements can also be made in this area for Turkey with a different set of policy mechanisms over vehicle fleet. Based on these two factors (rail emission factor and fuel economy), two levels for SMM scenarios are generated, which are as follows:

(1) **SMM-1**: rail emission factor will reduce by 5% from its level in 2015 to 2025 and fuel economy of cars, taxis and shuttles will reduce by an extra 5% from its expected level in 2025.

(2) **SMM-2**: rail emission factor will reduce by 10% from its level in 2015 to 2025 and fuel economy of cars, taxis and shuttles will reduce by an extra 10% from its expected level in 2025.

2.3.3. Travel demand management (TDM)

Travel demand management covers policies including congestion charging, fuel tax, awareness campaigns or policies based on different incentives and disincentives to switch from cars to PT, walking and cycling, and to control the trip lengths. In our study, transportation cost and trip lengths are concerned with only. As some TDM policies aim to increase the cost for transportation to reduce the overall demand for travel, transportation cost variable is considered in our model to reflect such changes in the cost for transport as a result of the TDM policies that are applicable to the city. Similarly, some TDM policies aim to control or reduce trip lengths of the city residents, so the overall impact of such policies is considered by reflecting their potential changes on trip lengths in our model. Based on these, two levels for TDM based scenarios are generated, which are as follows:

(1) **TDM-1**: The transportation cost will increase an additional 20% per year from its expected level between 2015 and 2025, which will decrease the desire to drive ratio by 20% over the same period. Trip lengths of cars, taxis, and shuttles will reduce 10% per year from their expected levels over the period 2015-2025.

(2) **TDM-2**: The transportation cost will increase an additional 30% per year from its expected level between 2015 and 2025, which will make the desire to drive ratio will

decrease by 30% over the same period. Trip lengths of cars, taxis, and shuttles will reduce 15% per year from their expected levels over the period 2015-2025.

2.3.4. Integrated scenario (IS)

The city authorities may choose to invest both in supply and demand side policies simultaneously. Therefore, two different scenarios for integrating SMM and TDM scenarios are considered, which are as follows:

(1) **IS-1**: the combination of SMM-1 and TDM-1

(2) **IS-2**: the combination of SMM-2 and TDM-2

In total, there are seven different scenarios (BAU, SMM-1, SMM-2, TDM-1, TDM-2, IS-1, IS-2) to be tested using our SD model so that they can be compared with each other and find out the best scenario option. It should be noted that the considered policies and scenarios are recommended as neither the best policies nor the best scenarios. Alternatively, it is intended to illustrate a realistic assessment of the potential transport policies that can offer noteworthy contributions to energy conservation and CO2 mitigation in the city. Therefore, the reduction and increased percentages for the considered policies are determined in a way that they should be in a realistic range and similar to those of the previous studies (Guzman and Orjuela, 2017; Han and Hayashi, 2008; Xue Liu et al., 2015).

3. Results and discussions

3.1. Model validation

Model validation is a critical step to ensure the accuracy and reliability of the developed model with actual statistics. Thus, we perform a validation study by comparing the historical (actual) values with the simulated ones for the period between 2000 and 2015. The examined variables, herein, are our reference points: energy consumption and CO_2 emissions. The behaviors are analyzed using these two variables based on existing socioeconomic and mobility conditions. The formulas defined in the previous section are used to calculate energy consumption and associated CO_2 emissions for the existing values because there are not any particular data available for these two variables. Table 4 demonstrates the outcomes of this validation process with associated error rates. Differences may be caused for two reasons. First, a certain margin error occurs due to data fitting of system variables using variety of mathematical statistical approaches.

Second, errors can also be amplified from the interaction of effects between different variables in the model during the running process (Wen et al., 2016). As depicted in Table 4, the error rates for both energy consumption and CO_2 emissions are all under 1%. That being said, it can be concluded that the developed model appears to be reliable and accurate for the purpose of our study (Qudrat-Ullah and Seong, 2010; Wang et al., 2008).

Table 4: Energy consumption and CO_2 emissions simulated results with historical values and error rates

Year	Total energy consumption (kiloliters of oil equivalent)			Total CO_2 emissions (metric tons)		
	Historical	Simulated	Error (%)	Historical	Simulated	Error (%)
2000	1,039,572	1,030,943	0.83	2,584,258	2,562,980	0.82
2001	1,097,029	1,090,534	0.59	2,728,906	2,712,890	0.59
2002	1,192,777	1,188,193	0.38	2,967,071	2,955,770	0.38
2003	1,268,078	1,270,938	-0.23	3,153,832	3,160,890	-0.22
2004	1,413,384	1,402,735	0.75	3,515,662	3,489,400	0.75
2005	1,490,759	1,483,629	0.48	3,709,821	3,692,240	0.47
2006	1,561,453	1,558,778	0.17	3,889,901	3,883,300	0.17
2007	1,726,581	1,728,929	-0.14	4,304,012	4,309,800	-0.13
2008	1,798,952	1,784,918	0.78	4,486,241	4,451,640	0.77
2009	1,888,996	1,878,881	0.54	4,708,039	4,683,100	0.53
2010	1,909,202	1,909,188	0.001	4,759,934	4,759,900	0.001
2011	1,995,655	2,001,944	-0.32	4,977,927	4,993,440	-0.31
2012	2,122,658	2,104,893	0.84	5,298,617	5,254,810	0.83
2013	2,245,997	2,232,249	0.61	5,626,404	5,581,980	0.79
2014	2,365,039	2,357,143	0.33	5,931,960	5,912,790	0.32
2015	2,506,596	2,509,726	-0.12	6,298,309	6,308,160	-0.16

3.2. Business as usual scenario (BAU)

Future predictions under BAU scenario were obtained using our developed SD model. In this scenario, the expected modal share between the years 2016 and 2025 is shown in Figure 5. The share of rail transit trips in this figure shows a sharply rising trend from its share of 10.7 % in 2016 to a share of 25.3% in 2025. Unlike rail transit, the share of road-based public transportation trips composed of bus, shuttle, minibus, jitney and taxi trips shows a dramatic declining trend from its share of 53.3% in 2016 to a share of 35.9% in 2025. On the other hand, the share of car trips rises from 34% in 2016 to 38% in 2025 over the same period. Furthermore, the share of trips made by sea lines also declines over the same period from 1.2% in 2016 to 0.5% in 2025. These figures are parallel with the development plans of the city where a large proportion of the investment budgets is devoted to expanding the rail network in the city. However, it is also important to point out that the increase in the share of car trips is due to the rapidly increasing personal motorization trend, which has been already at alarming levels. Therefore, the Istanbul urban passenger motorized trips may move away from the target of reaching sustainable transportation, especially when considering the modal share, where the car will still be a leading component.

The expected energy consumption and associated CO_2 emissions per capita in motorized passenger transport in the city between 2016 and 2025 are provided in Figure 6. As depicted in this figure, energy consumption per capita is expected to increase by 72% from 183 liters of oil equivalent in 2016 to 315 liters of oil equivalent in 2025. Similarly, CO_2 emissions per capita are expected to increase by 76% over the same period from their level of 460 kg in 2016 to 807 kg in 2025. These dramatic increases are directly associated with the expected increase in total motorized passenger trips and trip lengths. Between 2016 and 2025, the number of daily motorized passenger trips is expected to increase from approximately 16.32 million in 2016 to 29.43 million in 2025, with an increase of 80%. Over the same period, it is also estimated that trip lengths for all transportation means are expected to increase approximately 30% on average.

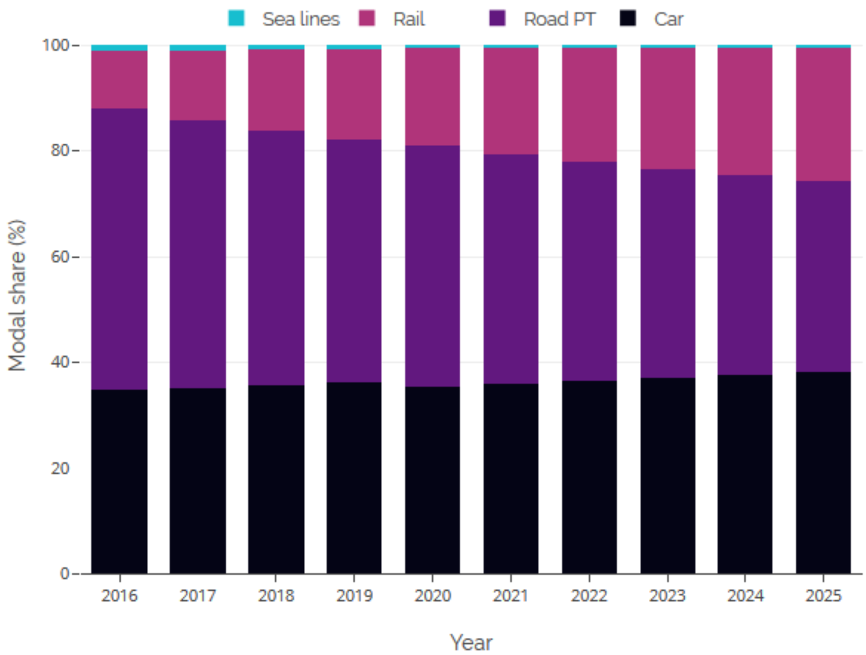

Figure 5: Modal share (%) in Istanbul under BAU scenario (2016-2025)

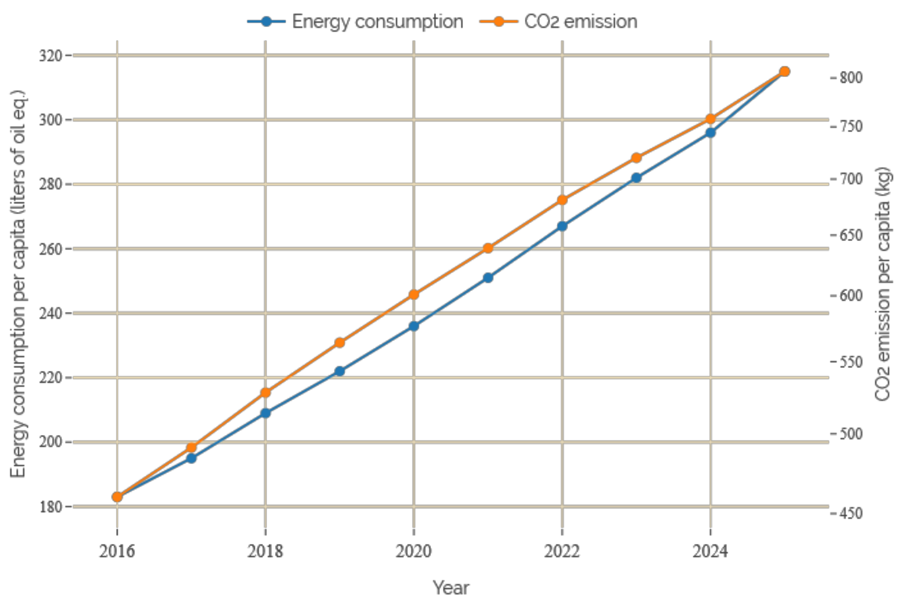

Figure 6: Energy consumption and CO_2 emissions per capita under the BAU scenario (2016-2025)

A noteworthy result of the BAU scenario is that the contribution of car trips to total energy consumption and CO_2 emissions shows a rising trend, despite the planned considerable investments in rapid transit including the railway and BRT networks (see Figure 7 and 8). While car trips account for 69% of total energy consumption and 70% of CO_2 emissions in 2016, they are expected to account for 80% of total energy consumption and 77% of CO_2 emissions in

2025. On the other hand, the share of non-road based trips (rail and sea) shows a rising pattern; however, this does not seem enough to hinder the pressure of rapidly increasing car trips on energy consumption and CO_2 emissions. This suggests that much more effort is needed to manage the passenger transport in the city in terms of reducing energy consumption and CO_2 emissions to achieve sustainable mobility goals.

The results of BAU scenario indicate that current development plans will have a minimal overall impact on the transport caused energy consumption and CO_2 emissions in the city because of the increasing number of motorized trips and trip lengths, especially from cars. Hence, greater effort is needed to better control these figures, and to this end, different sets of policies can be employed.

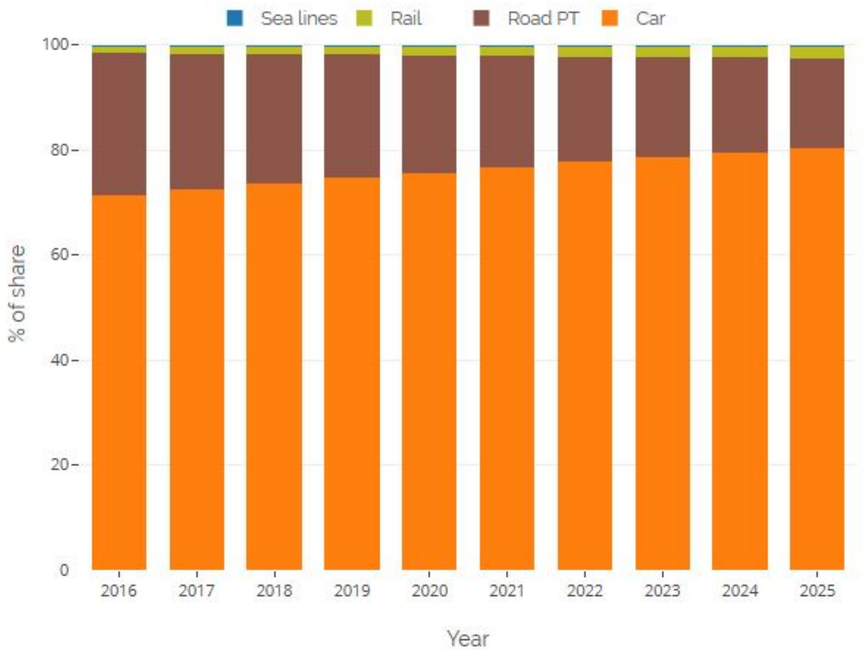

Figure 7: Percent share of modes in total energy consumption (2016-2025)

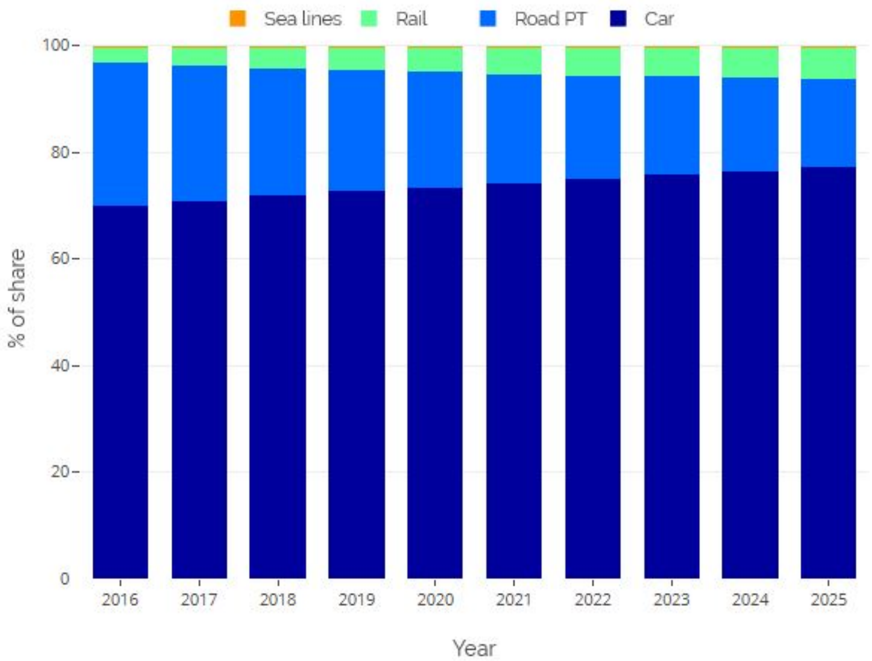

Figure 8: Percent share of modes in total CO_2 emissions (2016-2025)

3.3. Comparison and evaluation of proposed scenarios

Our model was run under the generated scenarios as explained above. For the year 2025, the expected total energy consumption and associated CO_2 emission levels of each scenario are provided in Figure 9. The sequence from the least effective to the most in terms of both energy consumption and CO_2 emissions is SMM-1, SMM-2, TDM-1, IS-1, TDM-2, and IS-2. The reduction percentages of these scenarios compared to the BAU scenario can be seen in Figure 9. Scenarios only based on supply-side measures, SMM-1 and SMM-2, appear to be the least effective among the other options with reduction rates of 4.6% and 9.0% in energy consumption and 4.7% and 9.3% in CO_2 emissions, respectively. This might be because additional improvements are more difficult to realize on the technological side. On the other hand, TDM-based scenarios, TDM-1 and TDM-2, perform better in further reducing energy consumptions and emissions. As TDM-2 scenario offers a 27.2% reduction in total energy consumption and a 26.2% reduction in total CO2 emissions, it is even better than the combined IS-1 scenario, which is composed of SMM-1 and TDM-1. This suggests how effective TDM policies can be in reducing the transport sector's energy consumption and associated CO_2 emissions in a megacity. Especially considering the fact that the evolution of demand-side policy interventions in the transport sector of Istanbul is in a very early stage (Batur & Koç, 2017), TDM measures should be taken into consideration in all ways and means to mitigate the increasing levels of energy consumption and CO_2 emissions.

As expected, the results indicate the most effective scenario option as IS-2, which is composed of ambitious scenario options of SMM and TDM, and which shows a reduction rate of 33.5% in energy consumption and 32.8% in CO_2 emissions in 2025 compared to the BAU scenario. The results show that IS-2 can reduce the total energy consumption in 2025 by as much as 1.8 billion liters of oil equivalent while it can cut CO_2 emission levels by as much as 4.5 billion kg. From the standpoint of per capita values, if the IS-2 scenario is to be implemented by 2025, the energy consumption per capita will be 209 liters of oil equivalent while CO_2 emissions per capita would be 542 kg. In other words, IS-2 has the potential to bring energy consumption and CO_2 per capita levels in 2025 to the levels of the BAU scenario in 2018.

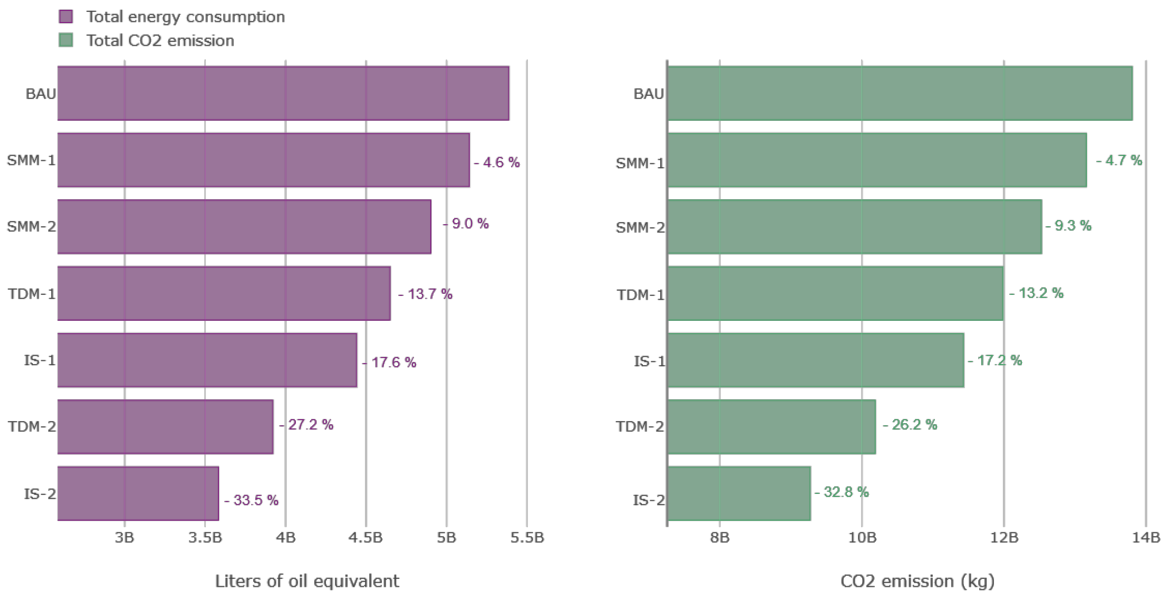

Figure 9: Total energy consumption and CO_2 emissions in 2025 under different scenarios

In addition, it is important to address the modal shares for these scenarios. Returning briefly to the subject of scenario generation, the fuel economy of vehicles, rail emission factor, transportation cost, and trip lengths have been concerned with when generating our scenarios, SMM-1, SMM-2, TDM-1, TDM-2, IS-1, and IS-2. Among these, only transportation cost plays a role in changing modal share figures compared to the BAU scenario, through which desire to drive ratio is affected, and thus annual passenger trips per car. Given that it has been considered in TDM scenarios, it did not affect the modal share in SMM scenarios at all. As presented in Table 3, transportation cost has a very limited effect on changing the modal shares of TDM and IS scenarios. The reasons behind this might be that the perceived attractiveness of personal car usage could be so high that 15% to 30% increase in transportation cost does not influence much the mode choice of people. Similarly, the conditions and availability of alternative modes (e.g., safety, speed, crowd, reliability, and adequacy) could be so poor that people still tend to choose personal cars over the other modes. This indicates that much more effort needed other than increasing transportation cost to tackle with increasing personal car usage in the city.

Table 3: Modal Shares in 2025 under different scenarios

Scenarios	Road PT	Rail	Sea Lines	Car
BAU	35.97%	25.27%	0.51%	38.24%
SMM-1	35.97%	25.27%	0.51%	38.24%
SMM-2	35.97%	25.27%	0.51%	38.24%
TDM-1	36.01%	25.30%	0.51%	38.24%
TDM-2	36.03%	25.31%	0.51%	38.24%
IS-1	36.01%	25.30%	0.51%	38.24%
IS-2	36.03%	25.31%	0.51%	38.24%

Above all, the results of BAU scenario clearly shows that current development plans with a particular focus on rail network expansion will fall short of combatting ever-increasing energy consumption and CO_2 emissions in the city because of the increasing number of personal vehicles, motorized trips, and trip lengths. The comparison results of proposed scenarios indicate how supply-side measures (i.e., improved fuel economy of vehicles and reduced rail emission factor) had a limited effect on the total energy consumption and associated CO_2 emissions of the transport sector for the city compared to demand-side measures (i.e., increased transportation cost and reduced trip lengths) with a noteworthy potential in this regard. These results show consistency with earlier research (see Gross et al., 2009) that highlights the significant potential for energy conservation and associated CO_2 emissions savings from demand-side policies. As future steps to decrease energy consumption and CO2 emissions are required for making cities more livable and adaptable to sustainable development, these results suggest that the policymakers in the city should give the highest priority to all demand-side policies that aim to control the vehicle ownership rates (through increasing transportation cost) and reduce the trip lengths. According to the results, additional improvements can be achieved by investing in the supply-side policies that aim to improve rail emission factor and fuel economy of vehicle fleet; thus, such policies should also be accounted in devising appropriate transport policies for the city. In the case of unlimited or large budgets for investments, the policymakers can consider all policies from both categories, the supply-side and the demand-side as the IS-2 scenario promises the most significant impact. Furthermore, these results also apply to the similar cities of the developing world that they should prioritize demand-side policies to mitigate energy consumption and CO2 emissions as their contributions are more than those of the supply-side policies are although the supply-side policies show a significant impact.

3.4. Sensitivity analysis

Furthermore, a sensitivity analysis is carried out to test the robustness of the developed model with respect to the changes in the varying parameters. Numerous parameters are considered that might have a subtle effect on total energy consumption and total CO_2 emissions that are the variables of interest. Because there is a linear relationship between total energy consumption and total CO_2 emissions, a parameter that is sensitive to any of these two variables is also sensitive to the other one. For this, the total CO_2 emissions variable is considered only in our analyses. In order to conduct the analysis, the values of the selected parameters are changed within ±20% of their ranges and the changes in total CO_2 emissions are observed. Table 4 presents the results of the sensitivity analysis. As observed from the results, the selected parameters are all sensitive to total CO_2 emissions in different ranges. In particular, GDP growth rate indicates low-sensitivity and transportation cost indicate mid-sensitivity, while the other parameters are found highly sensitive to total CO_2 emissions.

Table 4: Sensitivity analysis results of the selected parameters

Parameter	Test range	Sensitivity to total CO_2 emissions
Population growth rate (%)	1.11 – 2.33	High-sensitivity; sensitivity remains stable over time

GDP growth rate (%)	-0.27 – 56	Low-sensitivity; sensitivity increases over time
Transportation cost (Turkish Lira)	37.6 – 278.4	Mid-sensitivity; sensitivity increases over time
Rail length increase (km)	0 – 29.46	High sensitivity; sensitivity remains stable over time
# of rail transit passengers increase per km (person)	-415,200 – 710,040	High sensitivity; sensitivity remains stable over time
BRT length increase (km)	0 – 21.96	High sensitivity; sensitivity remains stable over time
# of BRT passengers increase per km (person)	-554,560 – 1,933,200	High sensitivity; sensitivity remains stable over time
Bus fleet in operation (vehicle)	3040 – 6862	High sensitivity; sensitivity remains stable over time
Trip growth per bus (trip)	-11,160 – 33,300	High sensitivity; sensitivity remains stable over time
Minibus trips growth rate (%)	-10.2 – 16.9	High sensitivity; sensitivity remains stable over time
Shuttle trips growth rate (%)	-0.47 – 18	High sensitivity; sensitivity remains stable over time
Taxi trip length (km)	4.99 – 14.52	High sensitivity; sensitivity remains stable over time
Taxi energy cons. per trip*km (liters of oil)	0.056 – 0.12	High sensitivity; sensitivity remains stable over time
Car trip length (km)	6.89 – 20.02	High sensitivity; sensitivity remains stable over time
Car energy cons. per trip*km (liters of oil)	0.044 – 0.098	High sensitivity; sensitivity remains stable over time
Shuttle trip length (km)	7.68 – 22.87	High sensitivity; sensitivity remains stable over time

Shuttle energy cons. per trip*km (liters of oil)	0.088 – 0.168	High sensitivity; sensitivity remains stable over time

4. Conclusion

The current paper first predicts future energy consumption and CO_2 emissions caused by motorized passenger transport in Istanbul using a developed SD model. Following, the developed model is used to test and propose appropriate scenarios in reducing expected levels of energy consumption and CO_2 emissions in the city. In order to that, six scenarios are generated based on various supply management and travel demand management measures, which are then tested and compared with the BAU scenario. The generated scenarios based on supply-side measures are SMM-1 and SMM-2, which include different reduction targets on the levels of rail emission factor and fuel economy of the vehicle fleet. On the other hand, the generated demand side scenarios are TDM-1 and TDM-2, which include increases in transportation cost and reductions in trip lengths. The last two scenario options are IS-1 and IS-2 hereby IS-1 is based on implementing SMM-1 and TDM-1 simultaneously while IS-2 combines SMM-2 and TDM-2.

Under BAU scenario, the results show that energy consumption per capita from passenger trips is expected to increase from 183 liters of oil equivalent in 2016 to 315 liters of oil equivalent in 2025 while CO_2 emissions per capita are expected to increase from 460 kg in 2016 to 807 kg in 2025. This dramatic increase is directly associated with the increasing level of car trips, trip lengths and overall travel demand in the city. In this point, the generated scenarios offer noteworthy potential in combating these dramatic increases in energy consumption and CO_2 emissions, with expected reduction rates ranging between 4% and 34% in both categories. Among the stand-alone scenario options, travel demand management based scenarios outperform supply management measures based scenarios. The reduction percentages of TDM based scenarios in terms of both energy consumption and CO_2 emissions range from 13% to 27% while the reduction percentages for SMM based scenarios range from 4% to 9%. Among the considered policies, this suggests that the policies from the demand side are more effective than the policies from the supply side.

Furthermore, the results suggested that the IS-2 scenario is the best scenario option among all the considered scenarios by offering a 33.5% reduction in total energy consumption and a 32.8% reduction in total CO2 emissions while the other integrated scenario (IS-1) offers a 17.6% reduction in total energy consumption and 17.2% reduction in CO2 emissions in 2025. Although IS-2 achieves the lowest levels of energy consumption and CO2 emissions, TDM-2 scenario shows a similar performance with IS-2 as it offers a 27.2% reduction in total energy consumption and a 26.2% reduction in total CO2 emissions. Moreover, the demand side policies can be even more effective than combining the supply side and demand side policies as TDM-2 scenario outperforms IS-1 scenario. This suggests that demand-side policies can be very effective in reducing the transport sector's energy consumption and associated CO2 emissions in a mega-city. Therefore, it is recommended that giving priority to TDM policies is essential in developing an intervention plan to combat increasing energy consumption and CO2 emissions in the transport sector.

One might raise particular concerns regarding the developed model for this study. One concern might be the exclusion of public transportation service level from our model, which possibly affects the travel choices of people in terms of punctuality, comfort, and reliability. However, it is believed that service level of public transportation does not have a major effect in the travel choice of inhabitants in the city within the current situation because the capacity usage of PT services is very high. For instance, the BRT system has been operating over-capacity ever since it started. In addition to that, there is not enough data on these factors; therefore, it has been decided to exclude them. Another possible concern is the exclusion of investment budgets towards different transport means, which is an important factor in expanding network length and service of any means of transport available in the city. The quality and sufficiency of data on this factor are not enough to determine the relationships with the other factors included in the model, and thus it was also excluded. On the other hand, policies on demand side were considered, which only concerned reducing overall trip lengths without taking into account trip purposes. However, people travel for different purposes and it is better to devise appropriate policies for each trip purpose such as workplace travel plans, school travel plans, online shopping and car clubs. Further research in this field would be of great help in overcoming the aforementioned possible shortcomings and limitation of this study.

5. Appendices

Appendix A: See Figures A1 and A2.

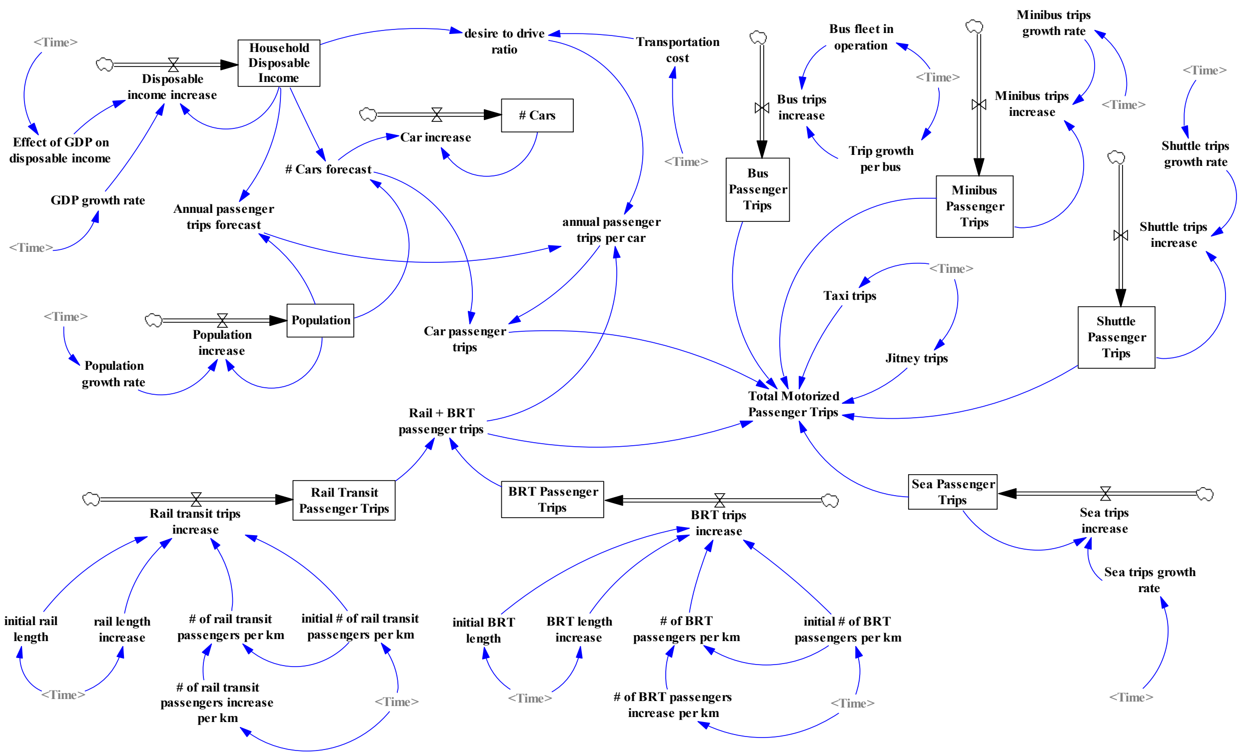

Figure A-1: Stock and flow diagram of the population, household disposable income and transport subsystems

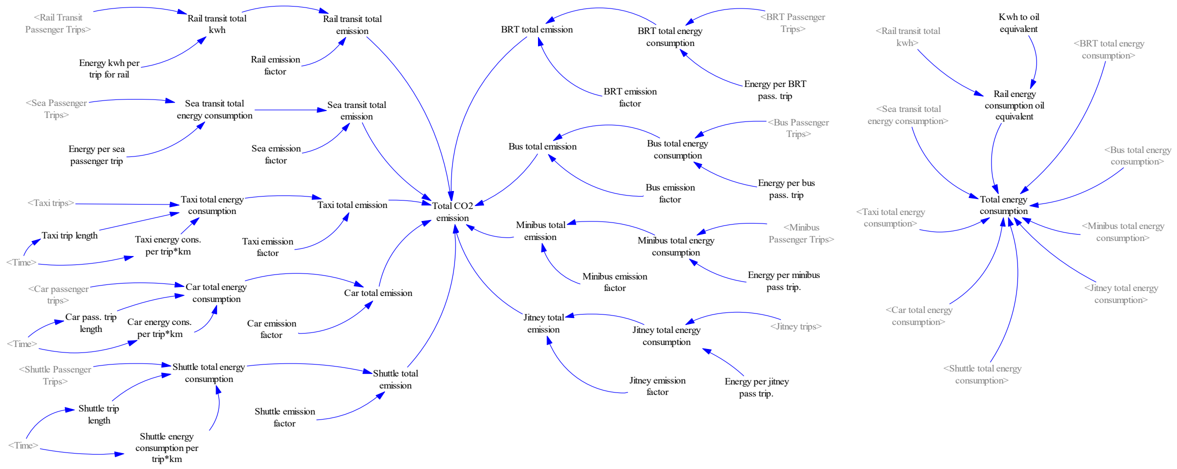

Figure A-2: Stock and flow diagram of the energy consumption and CO_2 emissions subsystem

Appendix B: List of variables

Population subsystem:

(1) Population growth rate
(Type: Auxiliary, Unit: Percent) (Turkstat, 2016c)

(2) Population increase = Population × Population growth rate
(Type: Flow, Unit: Person)

(3) Population = INTEG(Population increase) + initial population value
(Type: Stock, Unit: Person)

Household disposable income subsystem:

(1) GDP growth rate
(Type: Auxiliary, Unit: Percent) (PWC, 2009; TEPAV, 2016)

(2) Effect of GDP on disposable income
(Type: Auxiliary, Unit: Dimensionless) (Turkstat, 2016d)

(3) Disposable income increase = Household Disposable Income × Effect of GDP on disposable income × GDP growth rate
(Type: Flow, Unit: Turkish Lira)

(4) Household disposable income = INTEG(Disposable income increase) + initial income value
(Type: Stock, Unit: Turkish Lira)

Transport subsystem:

(1) # Cars forecast = 2.65096E+006 – (Population × 0.15039) + (Household Disposable Income × 120.853)
(Type: Auxiliary, Unit: Vehicle) (Turkstat, 2016b)

(2) Car increase = # Cars forecast + # Cars
(Type: Flow, Unit: Vehicle)

(3) # Cars = INTEG(Car increase)
(Type: Stock, Unit: Vehicle)

(4) Transportation cost
(Type: Auxiliary, Unit: Turkish Lira) (Turkstat, 2016d)

(5) Desire to drive ratio = Household disposable income / Transportation cost
(Type: Auxiliary, Unit: Dimensionless)

(6) Annual passenger trips forecast = −1.44999E+009 + (382.38 × Population) + (100380 × Household disposable income)
(Type: Auxiliary, Unit: Trip)

(7) Annual passenger trips per car = 709.033 − (1.00929E−008 × Rail+BRT passenger trips) + (0.330705 × Desire to drive ratio) + (9.0247E-009 × Annual passenger trips forecast)
(Type: Auxiliary, Unit: Trip)

(8) Rail+BRT passenger trips = BRT Passenger Trips + Rail Transit Passenger Trips
(Type: Auxiliary, Unit: Trip)

(9) Car passenger trips = # Cars forecast × Annual passenger trips per car
(Type: Auxiliary, Unit: Trip)

(10) Initial rail length
(Type: Auxiliary, Unit: Kilometer) (IMM, 2018a)

(11) Rail length increase
(Type: Auxiliary, Unit: Kilometer) (IMM, 2018a)

(12) # of rail transit passengers increase per km
(Type: Auxiliary, Unit: Person) (IMM, 2018a)

(13) Initial # of rail transit passengers per km
(Type: Auxiliary, Unit: Person) (IMM, 2018a)

(14) # of rail transit passengers per km = # of rail transit passengers increase per km + initial # of rail transit passengers per km
(Type: Auxiliary, Unit: Person)

(15) Rail transit trips increase = Rail length increase × # of rail transit passengers per km + Initial rail length × (# of rail transit passengers per km − Initial # of rail transit passengers per km)
(Type: Flow, Unit: Trip)

(16) Rail transit passenger trips = INTEG(Rail transit trips increase) + initial rail transit trips value
(Type: Stock, Unit: Trip)

(17) Initial BRT length
(Type: Auxiliary, Unit: Kilometer) (IMM, 2018a)

(18) BRT length increase
(Type: Auxiliary, Unit: Kilometer) (IMM, 2018a)

(19) # of BRT passengers increase per km
(Type: Auxiliary, Unit: Person) (IMM, 2018a)

(20) Initial # of BRT passengers per km
(Type: Auxiliary, Unit: Person) (IMM, 2018a)

(21) # of BRT passengers per km = # of BRT passengers increase per km + Initial # of BRT passengers per km
(Type: Auxiliary, Unit: Person)

(22) BRT trips increase = BRT length increase × # of BRT passengers per km +Initial BRT length × (# of BRT passengers per km − Initial # of BRT passengers per km)
(Type: Flow, Unit: Trip)

(23) BRT passenger trips = INTEG(BRT trips increase) + initial BRT trips value
(Type: Stock, Unit: Trip)

(24) Bus fleet in operation
(Type: Auxiliary, Unit: Vehicle) (IETT, 2017b)

(25) Trip growth per bus
(Type: Auxiliary, Unit: Trip) (IETT, 2017b)

(26) Bus trips increase = Bus fleet in operation × Trip growth per bus
(Type: Flow, Unit: Trip)

(27) Bus passenger trips = INTEG(Bus trips increase) + initial bus trips value
(Type: Stock, Unit: Trip)

(28) Minibus trips growth rate
(Type: Auxiliary, Unit: Percent) (IETT, 2017b)

(29) Minibus trips increase = Minibus passenger trips × Minibus trips growth rate
(Type: Flow, Unit: Trip)

(30) Minibus passenger trips = INTEG(Minibus trips increase) + initial minibus trips value
(Type: Stock, Unit: Trip)

(31) Shuttle trips growth rate
(Type: Auxiliary, Unit: Percent) (IMM, 2015, 2011)

(32) Shuttle trips increase = Shuttle passenger trips × Shuttle trips growth rate
(Type: Flow, Unit: Trip)

(33) Shuttle passenger trips = INTEG(Shuttle trips increase) + initial shuttle trips value
(Type: Stock, Unit: Trip)

(34) Sea trips growth rate
(Type: Auxiliary, Unit: Percent) (Çancı et al., 2015; IMM, 2015, 2011)

(35) Sea trips increase = Sea passenger trips × Sea trips growth rate
(Type: Flow, Unit: Trip)

(36) Sea passenger trips = INTEG(Sea trips increase) + initial sea trips value
(Type: Stock, Unit: Trip)

(37) Taxi trips
(Type: Auxiliary, Unit: Trip) (IMM, 2015, 2011)

(38) Jitney trips
(Type: Auxiliary, Unit: Trip) (IMM, 2015, 2011)

(39) Total motorized passenger trips = Car passenger trips + Rail+BRT passenger trips + Bus passenger trips + Minibus passenger trips + Shuttle passenger trips + Sea passenger Trips + Taxi trips + Jitney trips
(Type: Auxiliary, Unit: Trip)

Energy consumption and CO_2 emissions subsystem:

(1) Energy kwh per trip for rail
(Type: Auxiliary, Unit: Kilowatt hour per trip) (IMM, 2018a)

(2) Rail transit total kwh = Energy kwh per trip for rail × Rail transit passenger trips
(Type: Auxiliary, Unit: Kilowatt hour)

(3) Rail emission factor
(Type: Auxiliary, Unit: Kilogram CO_2 per kilowatt hour) (EIGM, n.d.)

(4) Rail transit total emission = Rail emission factor × Rail transit total kwh
(Type: Auxiliary, Unit: Kilogram CO_2)

(5) Energy per sea passenger trip
(Type: Auxiliary, Unit: Liter of oil) (IMM, 2018b)

(6) Sea transit total energy consumption = Energy per sea passenger trip × Sea passenger trips
(Type: Auxiliary, Unit: Liter of oil)

(7) Sea emission factor
(Type: Auxiliary, Unit: Kilogram CO_2 per liter of oil) (IPCC, 2018)

(8) Sea transit total emission = Sea emission factor × Sea transit total energy consumption
(Type: Auxiliary, Unit: Kilogram CO_2)

(9) Taxi trip length
(Type: Auxiliary, Unit: Kilometer) (IMM, 2011)

(10) Taxi energy consumption per trip×km
(Type: Auxiliary, Unit: Liter of oil per trip×km) (GFEI, 2017)

(11) Taxi total energy consumption = Taxi trips × Taxi trip length × Taxi energy consumption per trip×km
(Type: Auxiliary, Unit: Liter of oil)

(12) Taxi emission factor
(Type: Auxiliary, Unit: Kilogram CO_2 per liter of oil) (IPCC, 2018)

(13) Taxi total emission = Taxi emission factor × Taxi total energy consumption
(Type: Auxiliary, Unit: Kilogram CO_2)

(14) Car trip length
(Type: Auxiliary, Unit: Kilometer) (IMM, 2011)

(15) Car energy consumption per trip×km
(Type: Auxiliary, Unit: Liter of oil per trip×km) (GFEI, 2017)

(16) Car total energy consumption = Car trips × Car trip length × Car energy consumption per trip×km
(Type: Auxiliary, Unit: Liter of oil)

(17) Car emission factor
(Type: Auxiliary, Unit: Kilogram CO_2 per liter of oil) (IPCC, 2018)

(18) Car total emission = Car emission factor × Car total energy consumption
(Type: Auxiliary, Unit: Kilogram CO_2)

(19) Shuttle trip length
(Type: Auxiliary, Unit: Kilometer) (IMM, 2011)

(20) Shuttle energy consumption per trip×km
(Type: Auxiliary, Unit: Liter of oil per trip×km) (GFEI, 2017)

(21) Shuttle total energy consumption = Shuttle trips × Shuttle trip length × Shuttle energy consumption per trip×km
(Type: Auxiliary, Unit: Liter of oil)

(22) Shuttle emission factor
(Type: Auxiliary, Unit: Kilogram CO_2 per liter of oil) (IPCC, 2018)

(23) Shuttle total emission = Shuttle emission factor × Shuttle total energy consumption
(Type: Auxiliary, Unit: Kilogram CO_2)

(24) Energy per BRT passenger trip
(Type: Auxiliary, Unit: Kilowatt hour per trip) (IETT, 2017b)

(25) BRT total energy consumption = Energy per BRT passenger trip × BRT passenger trips
(Type: Auxiliary, Unit: Liter of oil)

(26) BRT emission factor
(Type: Auxiliary, Unit: Kilogram CO_2 per liter of oil) (IPCC, 2018)

(27) BRT total emission = BRT emission factor × BRT total energy consumption
(Type: Auxiliary, Unit: Kilogram CO_2)

(28) Energy per bus passenger trip
(Type: Auxiliary, Unit: Kilowatt hour per trip) (IETT, 2017b)

(29) Bus total energy consumption = Energy per bus passenger trip × Bus passenger trips
(Type: Auxiliary, Unit: Liter of oil)

(30) Bus emission factor
(Type: Auxiliary, Unit: Kilogram CO_2 per liter of oil) (IPCC, 2018)

(31) Bus total emission = Bus emission factor × Bus total energy consumption
(Type: Auxiliary, Unit: Kilogram CO_2)

(32) Energy per minibus passenger trip
(Type: Auxiliary, Unit: Kilowatt hour per trip) (Source: Authors)

(33) Minibus total energy consumption = Energy per minibus passenger trip × Minibus passenger trips
(Type: Auxiliary, Unit: Liter of oil)

(34) Minibus emission factor
(Type: Auxiliary, Unit: Kilogram CO_2 per liter of oil) (IPCC, 2018)

(35) Minibus total emission = Minibus emission factor × Minibus total energy consumption
(Type: Auxiliary, Unit: Kilogram CO_2)

(36) Energy per jitney passenger trip
(Type: Auxiliary, Unit: Kilowatt hour per trip) (Source: Authors)

(37) Jitney total energy consumption = Energy per jitney passenger trip × Jitney passenger trips
(Type: Auxiliary, Unit: Liter of oil)

(38) Jitney emission factor
(Type: Auxiliary, Unit: Kilogram CO_2 per liter of oil) (IPCC, 2018)

(39) Jitney total emission = Jitney emission factor × Jitney total energy consumption
(Type: Auxiliary, Unit: Kilogram CO_2)

(40) Kwh to oil equivalent = 0.0895
(Type: Auxiliary, Unit: Liter of oil per kilowatt hour)

(41) Rail energy consumption oil equivalent = Kwh to oil equivalent × Rain transit total kwh

(Type: Auxiliary, Unit: Liter of oil)

(42) Total energy consumption = Rail energy consumption oil equivalent + Sea transit total energy consumption + Taxi total energy consumption + Car total energy consumption + Shuttle total energy consumption + BRT total energy consumption + Bus total energy consumption + Minibus total energy consumption + Jitney total energy consumption
(Type: Auxiliary, Unit: Liter of oil)

(43) Total CO_2 emissions = Rail transit total emission + Sea transit total emission + Taxi total emission + Car total emission + Shuttle total emission + BRT total emission + Bus total emission + Minibus total emission + Jitney total emission
(Type: Auxiliary, Unit: Kilogram CO_2)

6. References

Abbas, K., Bell, M., 1994. System dynamics applicability to transportation modeling. Transp. Res. Part A Policy Pract.

Andrejszki, T., Gangonells, M., Molnar, E., Török, Á., 2014. ForFITS : a new help in transport decision making for a sustainable future. https://doi.org/10.3311/PPtr.7442

Armah, F.A., Yawson, D.O., Pappoe, A.A.N.M., 2010. A Systems Dynamics Approach to Explore Traffic Congestion and Air Pollution Link in the City of Accra, Ghana. Sustainability 2, 252–265. https://doi.org/10.3390/su2010252

Batur, İ., Koç, M., 2017. Travel Demand Management (TDM) case study for social behavioral change towards sustainable urban transportation in Istanbul. Cities 69, 20–35. https://doi.org/10.1016/j.cities.2017.05.017

Boarini, R., Johansson, Å., d'Ercole, M., 2006. Alternative measures of well-being.

Bristow, A.L., Tight, M., Pridmore, A., May, A.D., 2008. Developing pathways to low carbon land-based passenger transport in Great Britain by 2050. Energy Policy 36, 3427–3435. https://doi.org/10.1016/j.enpol.2008.04.029

Brueckner, J.K., 2005. Transport subsidies, system choice, and urban sprawl. Reg. Sci. Urban Econ. 35, 715–733. https://doi.org/10.1016/j.regsciurbeco.2005.01.001

Çancı, M., Önden, İ., Çakmak, E., Gürel, Ö., Tuzla, H., 2015. İstanbul'da Deniz Ulaşımının Geleceğinin Değerlendirilmesi. Istanbul.

Cao, J., Menendez, M., 2015. System dynamics of urban traffic based on its parking-related-states. Transp. Res. Part B Methodol. 81, 718–736. https://doi.org/10.1016/j.trb.2015.07.018

Cheng, Y.-H., Chang, Y.-H., Lu, I.J., 2015. Urban transportation energy and carbon dioxide emission reduction strategies. Appl. Energy 157, 953–973. https://doi.org/10.1016/j.apenergy.2015.01.126

Dargay, J., Gately, D., Sommer, M., 2007. Vehicle ownership and income growth, worldwide: 1960-2030. Energy J. 143–170.

Du, L., Li, X., Zhao, H., Ma, W., Jiang, P., 2018. System dynamic modeling of urban carbon emissions based on the regional National Economy and Social Development Plan : A case study of Shanghai city. J. Clean. Prod. 172, 1501–1513. https://doi.org/10.1016/j.jclepro.2017.10.128

Duran-Encalada, J., Paucar-Caceres, A., 2009. System dynamics urban sustainability model for Puerto Aura in Puebla, Mexico. Syst. Pract. action ….

Dyson, B., Chang, N., 2005. Forecasting municipal solid waste generation in a fast-growing urban region with system dynamics modeling. Waste Manag.

Egilmez, G., Tatari, O., 2012. A dynamic modeling approach to highway sustainability: Strategies to reduce overall impact. Transp. Res. Part A Policy Pract. 46, 1086–1096. https://doi.org/10.1016/j.tra.2012.04.011

EIGM, n.d. AYLIK ENERJİ İSTATİSTİKLERİ RAPORU-1.

EPDK, 2017. Energy Market Sector Reports.

Feng, C.-M., Hsieh, C.-H., 2009. Effect of Resource Allocation Policies on Urban Transport Diversity. Comput. Civ. Infrastruct. Eng. 24, 525–533. https://doi.org/10.1111/j.1467-8667.2009.00608.x

Feng, Y.Y., Chen, S.Q., Zhang, L.X., 2013. System dynamics modeling for urban energy consumption and CO2 emissions: A case study of Beijing, China. Ecol. Modell. 252, 44–52. https://doi.org/10.1016/j.ecolmodel.2012.09.008

Fong, W., Matsumoto, H., Lun, Y., 2009. Application of System Dynamics model as decision making tool in urban planning process toward stabilizing carbon dioxide emissions from cities. Build. Environ. 44, 1528–1537. https://doi.org/10.1016/j.buildenv.2008.07.010

Ford, A., 1997. System dynamics and the electric power industry. Syst. Dyn. Rev.

Forrester, J., 1970. Urban dynamics. IMR; Ind. Manag. Rev.

Forrester, J., 1958. Industrial dynamics: a major breakthrough for decision makers. Harv. Bus. Rev.

Forrester, J., Mass, N., Ryan, C., 1976. The system dynamics national model: understanding socio-economic behavior and policy alternatives. Technol. Forecast. Soc. ….

Gerçek, H., Demir, O., 2008. Urban Mobility in Istanbul. French Dev. Agency.

GFEI, 2017. INTERNATIONAL COMPARISON OF LIGHT-DUTY VEHICLE FUEL ECONOMY 2005-2015 Ten years of fuel economy benchmarking International comparison of light-duty vehicle fuel economy.

Goh, Y.M., Love, P.E.D., 2012. Methodological application of system dynamics for evaluating traffic safety policy. Saf. Sci. 50, 1594–1605. https://doi.org/10.1016/j.ssci.2012.03.002

Gross, R., Heptonstall, P., Anable, J., Greenacre, P., 2009. What policies are effective at reducing carbon emissions from surface passenger transport?-a review of interventions to encourage behavioural and technological.

Guzman, L.A., Orjuela, J.P., 2017. Linking a transport dynamic model with an emissions model to aid air pollution evaluations of transport policies in Latin America. Transp. B Transp. Dyn. 5, 270–285. https://doi.org/10.1080/21680566.2016.1169954

Haghshenas, H., Vaziri, M., Gholamialam, A., 2015. Evaluation of sustainable policy in urban transportation using system dynamics and world cities data: A case study in Isfahan. Cities 45, 104–115. https://doi.org/10.1016/j.cities.2014.11.003

Han, J., Hayashi, Y., 2008. A system dynamics model of CO2 mitigation in China's inter-city passenger transport. Transp. Res. Part D Transp. Environ. 13, 298–305.

https://doi.org/10.1016/j.trd.2008.03.005

Han, J., Hayashi, Y., Cao, X., Imura, H., 2009. Application of an integrated system dynamics and cellular automata model for urban growth assessment: A case study of Shanghai, China. Landsc. Urban Plan.

Hayter, R., 1997. The dynamics of industrial location: the factory, the firm, and the production system.

Homer, J., Hirsch, G., 2006. System dynamics modeling for public health: background and opportunities. Am. J. Public Health.

Huo, H., Wang, M., 2012. Modeling future vehicle sales and stock in China. Energy Policy 43, 17–29. https://doi.org/10.1016/j.enpol.2011.09.063

IEA, 2016. Key world energy statistics. Paris. Int. Energy Agency.

IETT, 2017a. Metrobüs [WWW Document]. URL http://metrobus.iett.istanbul/tr/metrobus (accessed 9.20.17).

IETT, 2017b. Public Transportation in Istanbul.

IMM, 2018a. Rail Systems in Istanbul.

IMM, 2018b. Şehir hatları.

IMM, 2015. Modal Split Statistics.

IMM, 2011. Istanbul Metropolitan Area Urban Transportation Master Plan, T. D. H. Office. Istanbul. Istanbul.

IPCC, 2018. 2006 IPCC Guidelines for National Greenhouse Gas Inventories [WWW Document]. URL https://www.ipcc-nggip.iges.or.jp/public/2006gl/ (accessed 10.10.17).

Kennedy, C.A., Stewart, I., Facchini, A., Cersosimo, I., Mele, R., Chen, B., Uda, M., Kansal, A., Chiu, A., Kim, K., Dubeux, C., Lebre La Rovere, E., Cunha, B., Pincetl, S., Keirstead, J., Barles, S., Pusaka, S., Gunawan, J., Adegbile, M., Nazariha, M., Hoque, S., Marcotullio, P.J., González Otharán, F., Genena, T., Ibrahim, N., Farooqui, R., Cervantes, G., Sahin, A.D., 2015. Energy and material flows of megacities. Proc. Natl. Acad. Sci. 112, 5985–5990. https://doi.org/10.1073/pnas.1504315112

Kumar, S., Yamaoka, T., 2007. System dynamics study of the Japanese automotive industry closed loop supply chain. J. Manuf. Technol. ….

Kwon, T., 2012. Strategic niche management of alternative fuel vehicles: A system dynamics model of the policy effect. Technol. Forecast. Soc. Change 79, 1672–1680. https://doi.org/10.1016/j.techfore.2012.05.015

Lane, D., Monefeldt, C., Rosenhead, J., 2000. Looking in the wrong place for healthcare improvements: A system dynamics study of an accident and emergency department. J. Oper. Res. ….

Lewe, J.-H., Hivin, L.F., Mavris, D.N., 2014. A multi-paradigm approach to system dynamics modeling of intercity transportation. Transp. Res. Part E Logist. Transp. Rev. 71, 188–202. https://doi.org/10.1016/j.tre.2014.09.011

Li, P., Zhao, P., Brand, C., 2018. Future energy use and CO2emissions of urban passenger transport in China: A travel behavior and urban form based approach. Appl. Energy 211, 820–842. https://doi.org/10.1016/j.apenergy.2017.11.022

Liu, S., Triantis, K.P., Sarangi, S., 2010. A framework for evaluating the dynamic impacts of a congestion pricing policy for a transportation socioeconomic system. Transp. Res. Part A Policy Pract. 44, 596–608. https://doi.org/10.1016/j.tra.2010.04.001

Liu, X., Ma, S., Tian, J., Jia, N., Li, G., 2015. A system dynamics approach to scenario analysis for urban passenger transport energy consumption and CO2 emissions: A case study of Beijing. Energy Policy 85, 253–270. https://doi.org/10.1016/j.enpol.2015.06.007

Liu, X., Mao, G., Ren, J., Li, R.Y.M., Guo, J., Zhang, L., 2015. How might China achieve its 2020 emissions target? A scenario analysis of energy consumption and CO2 emissions using the system dynamics model. J. Clean. Prod. 103, 401–410. https://doi.org/10.1016/j.jclepro.2014.12.080

Mandell, S., 2009. Policies towards a more efficient car fleet. Energy Policy 37, 5184–5191. https://doi.org/10.1016/j.enpol.2009.07.068

Menezes, E., Gori, A., Silva, C., Carvalho, D., 2017. Technological Forecasting & Social Change Effectiveness of low-carbon development strategies : Evaluation of policy scenarios for the urban transport sector in a Brazilian megacity ☆. Technol. Forecast. Soc. Chang. 114, 226–241. https://doi.org/10.1016/j.techfore.2016.08.016

Meyer, M.D., 1997. A Toolbox for Alleviating Congestion and Enhancing Mobility.

Moriarty, P., Honnery, D., 2008. Low-mobility: The future of transport. Futures 40, 865–872. https://doi.org/10.1016/j.futures.2008.07.021

OECD, 2008. OECD Territorial Reviews: Istanbul, Turkey - OECD.

Onat, N.C., Kucukvar, M., Tatari, O., Egilmez, G., 2016. Integration of system dynamics approach toward deepening and broadening the life cycle sustainability assessment framework: a case for electric vehicles. Int. J. Life Cycle Assess. 21, 1009–1034. https://doi.org/10.1007/s11367-016-1070-4

Pfaffenbichler, P., Emberger, G., Shepherd, S., 2010. A system dynamics approach to land use transport interaction modelling: The strategic model MARS and its application. Syst. Dyn. Rev. https://doi.org/10.1002/sdr.451

PWC, 2009. Which are the largest city economies in the world and how might this change by 2025?

Pye, S., Daly, H., 2015. Modelling sustainable urban travel in a whole systems energy model. Appl. Energy 159, 97–107. https://doi.org/10.1016/j.apenergy.2015.08.127

Qudrat-Ullah, H., Seong, B.S., 2010. How to do structural validity of a system dynamics type simulation model: The case of an energy policy model. Energy Policy 38, 2216–2224. https://doi.org/10.1016/j.enpol.2009.12.009

Royston, G., Dost, A., 1999. Using system dynamics to help develop and implement policies and programmes in health care in England. Syst. Dyn. ….

Sabounchi, N.S., Triantis, K.P., Sarangi, S., Liu, S., 2014. Dynamic simulation modeling and policy analysis of an area-based congestion pricing scheme for a transportation socioeconomic system. Transp. Res. Part A Policy Pract. 59, 357–383. https://doi.org/10.1016/j.tra.2013.11.007

Saeed, K., 1994. Development planning and policy design: a system dynamics approach.

Shen, Q., Chen, Q., Tang, B., Yeung, S., Hu, Y., Cheung, G., 2009. A system dynamics model for the sustainable land use planning and development. Habitat Int. 33, 15–25. https://doi.org/10.1016/j.habitatint.2008.02.004

Shepherd, S.P., 2014. A review of system dynamics models applied in transportation. Transp. B Transp. Dyn. 2, 83–105. https://doi.org/10.1080/21680566.2014.916236

Shields, K., Langer, H., 2009. European Green City Index: Assessing the environmental impact of Europe's major cities.

Sorensen, A., Okata, J., 2010. Megacities: urban form, governance, and sustainability.

Stepp, M.D., Winebrake, J.J., Hawker, J.S., Skerlos, S.J., 2009. Greenhouse gas mitigation policies and the transportation sector: The role of feedback effects on policy effectiveness. Energy Policy 37, 2774–2787. https://doi.org/10.1016/j.enpol.2009.03.013

Stopher, P.R., 2004. Reducing road congestion: A reality check. Transp. Policy 11, 117–131. https://doi.org/10.1016/j.tranpol.2003.09.002

Struben, J., Sterman, J.D., 2008. Transition Challenges for Alternative Fuel Vehicle and Transportation Systems. Environ. Plan. B Plan. Des. 35, 1070–1097. https://doi.org/10.1068/b33022t

Suryani, E., Chou, S.-Y., Chen, C.-H., 2010. Air passenger demand forecasting and passenger terminal capacity expansion: A system dynamics framework. Expert Syst. Appl. 37, 2324–2339. https://doi.org/10.1016/j.eswa.2009.07.041

TEPAV, 2016. TEPAV | TEPAV'dan İl Bazında Milli Gelir Tahmini... [WWW Document]. URL http://www.tepav.org.tr/tr/haberler/s/4052 (accessed 9.17.17).

Timilsina, G.R., Shrestha, A., 2009. Transport sector CO2 emissions growth in Asia: Underlying factors and policy options. Energy Policy 37, 4523–4539. https://doi.org/10.1016/J.ENPOL.2009.06.009

TOMTOM, 2016. Full ranking | TomTom Traffic Index [WWW Document]. URL https://www.tomtom.com/en_gb/trafficindex/list?citySize=LARGE&continent=ALL&country=ALL (accessed 8.3.17).

Turkstat, 2016a. Sustainable Development Indicators.

Turkstat, 2016b. Transport Statistics.

Turkstat, 2016c. Population Statistics.

Turkstat, 2016d. Income and Living Conditions Survey 2015.

UN-DESA, 2014. World urbanization prospects: The 2014 revision. UN.

UN-Habitat, 2016. Urbanization and development, emerging futures. World cities Rep.

UN-Habitat, 2012. Sustainable urbanization, thematic think piece. Dep. Econ. Soc. Aff. UN Dev. Program.

Vafa-Arani, H., Jahani, S., Dashti, H., Heydari, J., Moazen, S., 2014. A system dynamics modeling for urban air pollution: A case study of Tehran, Iran. Transp. Res. Part D Transp. Environ. 31, 21–36. https://doi.org/10.1016/j.trd.2014.05.016

Vensim, 2017. Vensim Software | Vensim [WWW Document]. URL http://vensim.com/vensim-software/#latest-release-8211-vensim-7 (accessed 10.16.17).

Wang, J.-F.J., Lu, H.-P.H., Peng, H., 2008. System dynamics model of urban transportation system and its application. J. Transp. Syst. Eng. Inf. Technol. 8, 83–89. https://doi.org/10.1016/S1570-6672(08)60027-6

Wen, L., Bai, L., 2017. System Dynamics Modeling and Policy Simulation for Urban Traffic: a Case Study in Beijing. Environ. Model. Assess. 22, 363–378. https://doi.org/10.1007/s10666-016-9539-x

Wen, L., Bai, L., Zhang, E., Weng, J., 2016. A system dynamics model for industrial carbon emissions in Baoding. Math. Comput. Model. Dyn. Syst. 22, 555–568. https://doi.org/10.1080/13873954.2016.1206025

Wu, T., Zhao, H., Ou, X., 2014. Vehicle Ownership Analysis Based on GDP per Capita in China: 1963–2050. Sustain. 2014, Vol. 6, Pages 4877-4899 6, 4877–4899. https://doi.org/10.3390/SU6084877

Yang, Y., Zhang, P., Ni, S., 2014. Assessment of the Impacts of Urban Rail Transit on Metropolitan

Regions Using System Dynamics Model. Transp. Res. Procedia 4, 521–534. https://doi.org/10.1016/j.trpro.2014.11.040